AD-A116 887 CARNEGIE-MELLON UNIV PITTSBURGH PA DEPT OF PSYCHOLOGY F/G 5/10
REPRESENTATIONAL TYPES: A TRICODE PROPOSAL.(U)
JUN 82 J R ANDERSON N00014-81-C-0335
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Representational Types: A Tricode Proposal

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This research was supported by the Personnel and Training Research Programs, Psychological Services Division, Office of Naval Research, under Contract No.: N00014-81-C-0335, Contract Authority Identification Number, NR No.: 157-465 to John Anderson.

unclassified

SECURITY CLASSIFICATION OF THIS P (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER Technical Report #ONR-82-1	2. GOVT ACCESSION NO. AD-A116 887	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Representational Types: A Tricode Proposal		5. TYPE OF REPORT & PERIOD COVERED Interim report
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) John R. Anderson		8. CONTRACT OR GRANT NUMBER(s) N00014-81-C-0335
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 157-465
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research Arlington, Virginia 22217		12. REPORT DATE June 10, 1982
		13. NUMBER OF PAGES 85
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

production systems	cognitive units	retrieval
knowledge representation	abstract propositions	pattern-matching
declarative memory	tri-code proposal	all-or-none memory
temporal strings	mixed hierarchies	partial matching
spatial images	storage	emergent properties

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Certain mental processes only apply to certain knowledge structures. It is proposed that we consider a distinct representation type to exist if a set of structures have the same processes defined on them. This principle is applied in a production system framework in which the relevant cognitive processes are those which interface declarative memory and production memory with working memory. Numerous empirical phenomena

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20.) Abstract (continued)

point to the existence of at least three representational types. There are temporal strings, which encode ordinal information about the sequence of a set of events, spatial images, which store information about the spatial configuration of a set of objects, and abstract propositions, which encode abstract relations among objects. These three types of knowledge are treated distinctly by the processes that match production conditions and execute production actions. However, the three types are treated rather similarly with respect to storage and retrieval from declarative memory. These storage and retrieval processes treat small knowledge chunks, called cognitive units, in an all-or-none manner.

19.) Key Words (continued)

linear orderings
mental rotation
tangled hierarchies

On the Importance of Representation

The thesis of this paper is that there are three types or codes of knowledge representation. There are temporal strings which encode the sequential structure of a set of events. There are spatial images which store information about the spatial configuration of objects. Finally, there are abstract propositions which encode abstract and semantically significant relations among objects. At a certain level this central thesis is hardly news. The common man certainly suspected the existence of temporal strings in the form of word sequences. Similarly, he suspected the existence of spatial images in the visual modality. If not the common man, at least philosophers have suspected something like abstract propositions for centuries.

However, what is common sense is often not scientific fact and this common-sense hypothesis has been rather resistant to precise scientific formulations. The dual-code hypothesis (e.g., Bower, 1972; Paivio, 1971) has been advanced which argued for visual and verbal codes something like the temporal and spatial codes proposed above. The propositional hypothesis has been advanced (e.g., Anderson & Bower, 1973; Chase & Clark, 1972; Kintsch, 1974; Norman & Rumelhart, 1975; Pylyshyn, 1973; Reed, 1974) which argued that there is a code very much like my abstract propositional code. These two hypotheses have usually been offered as competitors and a major issue has been which was correct. Generally, it was not considered that the truth might lie in the union of the two hypotheses (but see Anderson, 1980a; Baddeley, 1976; Kosslyn, 1980). In reviewing this debate I (Anderson, 1976, 1978) argued that it was fundamentally incapable of resolution. However, this negative conclusion only applies to the view of representation as notation. I will argue it does not extend to a view of representation as defined by process.

One important issue is to spell out in what sense one can advance a scientific hypothesis for a tri-code theory. A second issue concerns what are the assumptions of that theory. The third issue is what the evidence is for such a theory. This paper will address these three issues. I will try to be as brief as possible about the first issue, and focus on the second two which are where the real scientific content lies.

Representation: Structure or Process?

My negative conclusions (Anderson, 1976, 1978) about representation were based on the interpretation of representation as a theory about notation. It is possible, however, to define representations in terms of the processes that operate on them rather than the notations that express them. This is the point of view I want to adopt in this paper. It is the same idea as underlies the concept of data types in computer science. A knowledge structure has certain processes defined for it and other processes are undefined for that structure. To be somewhat more concrete, one structure might have a rotate and a draw process defined for it, but not first or insert process, while another structure might have an insert and first processes defined for it, but not a rotate or draw. To foreshadow, we might want to call the first structure an image and the second a string. In our theoretical discussion, we will need some notation for communicating the structures but this is merely notation for purpose of communication. The real theory of representation lies in the processes. We can think of the structures as "black boxes" on which certain processes will operate to produce results. The contents of the black boxes will determine these results and so we need a notation to specify their contents. However, the structure of our notation is not an assertion about the structure of the contents of these boxes.

A human mind at any point in time can be thought of as containing a large number, n, of knowledge structures encoding the many things known. Individual knowledge structures would correspond to different things known or different things encoded about the environment. The mental system also has some m processes that operate on these structures. In the abstract, we can imagine specifying which processes operate on which structures by a n x m matrix where each cell contains a 1 if that process is defined for that structure and a 0 otherwise. Logically, it is possible that this matrix could be a completely random array of 0's and 1's. However, it might turn out that there are many rows with the exact same pattern of 0's and 1's. That is, it might turn out that a large subset of the structures have exactly the same set of processes defined. Another large subset of structures might have another different (but perhaps overlapping) set of processes. It might be possible to partition the very large number of structures into a relatively small number of subsets on this basis.

It would be a noteworthy result if it were possible to so partition the knowledge structures on the basis of the processes defined upon them. It is certainly not an empirically vacuous outcome and tells us something

very important about the human mind. That is, there are certain representational types (an analogy to data types from computer science) and different types are to be defined in terms of different processes. In this paper, I will argue that there are at least three types (temporal string, spatial array, and abstract propositional); and I will discuss the evidence for each.

The important observation, then, is that if we look at the processes defined on the structures we can define representation type or code which is a more abstract concept than representational notations which have been the focus of the imagery debate. In Appendix 1 I review my formal proof (Anderson, 1978) that representational notations are subject to severe problems of indeterminacy but I also show there that representational types are not subject to these same indeterminacy results. A useful analogy is to the contrast between integers and floating point numbers which are distinct data types in most programming languages. A programmer does not really care about the internal representation of these numbers. For him, the significant factors are the differences in the operations he can perform on these two data types and differences in the speed of these operations.

I will be proposing the existence of three types within a variant of the ACT (Anderson, 1976) production system framework. It is only within such a general specification of an information-processing system that one can be relatively precise about the nature of processes that define the representational types. I think the arguments and evidence put forth here would have at least some informal force without specifying such a framework. However, with respect to an issue that has proven as slippery as representation, one should strive for as much precision as can be achieved.

The Production System Framework

According to Allen Newell (personal communication), production systems as a psychologically relevant idea developed in the mid-sixties at Carnegie-Mellon University. It seems clear that their technical origins derive from Post production systems (Post, 1943). It is probable (see Newell & Simon, 1972; Anderson, 1976) that production systems took some inspiration from both the strengths and weaknesses of stimulus-response learning theory. A number of publications in the early seventies were responsible for introducing them into the consciousness of psychology and artificial intelligence (e.g. Hunt & Poltrock, 1974; Newell, 1972, 1973;

Newell & Simon, 1973; Waterman, 1970). My own work on these systems has been in the context of the ACT theory (Anderson, 1976; 1983). There has been something of a divergence in the development of production systems with computer scientists developing specialized versions to facilitate knowledge engineering application and psychologically-minded folks sticking to more general conceptions. A conference on Pattern-Directed Inference Systems in 1977 was filled with confrontation between these two groups. The publications from this conference (Waterman & Hayes-Roth, 1978; and a special SIGART issue, 1977) presents much of this confrontation.

The production system framework that I will be assuming here for initial discussion is a more general version of the ACT production system. Figure 1 presents the schematic representation of this general architecture. The cognitive system has three essential components for present purposes -- a limited-capacity working memory that contains the current knowledge being operated upon, a production system that operates on the contents of working memory, and a general long-term declarative memory which contains facts that can be retrieved for use by working memory. This architecture is heretical from the point of view of the prototypical Newell system in that it has a separate declarative memory component. In the prototypical system there would only be production memory as a long-term memory base.

Insert Figure 1 about here

Working memory and long-term declarative memory are best conceived of as extensions of one another. Working memory contains in part information retrieved from long-term memory and in part new information which may or may not be encoded permanently in long-term memory. With respect to issues of knowledge representation I want to restrict myself to the structures that reside in working memory and long-term memory. The various arrows leading to and from working memory indicate some of the processes that interact intimately with these working memory structures. Therefore, they will be critical to my process interpretation of representation. Perception or encoding refers to the processes by which external stimuli become encoded into working memory structures. It is reasonable to suspect that there might be a strong connection between a theory of stimulus encoding and a theory of representation. One might well expect that

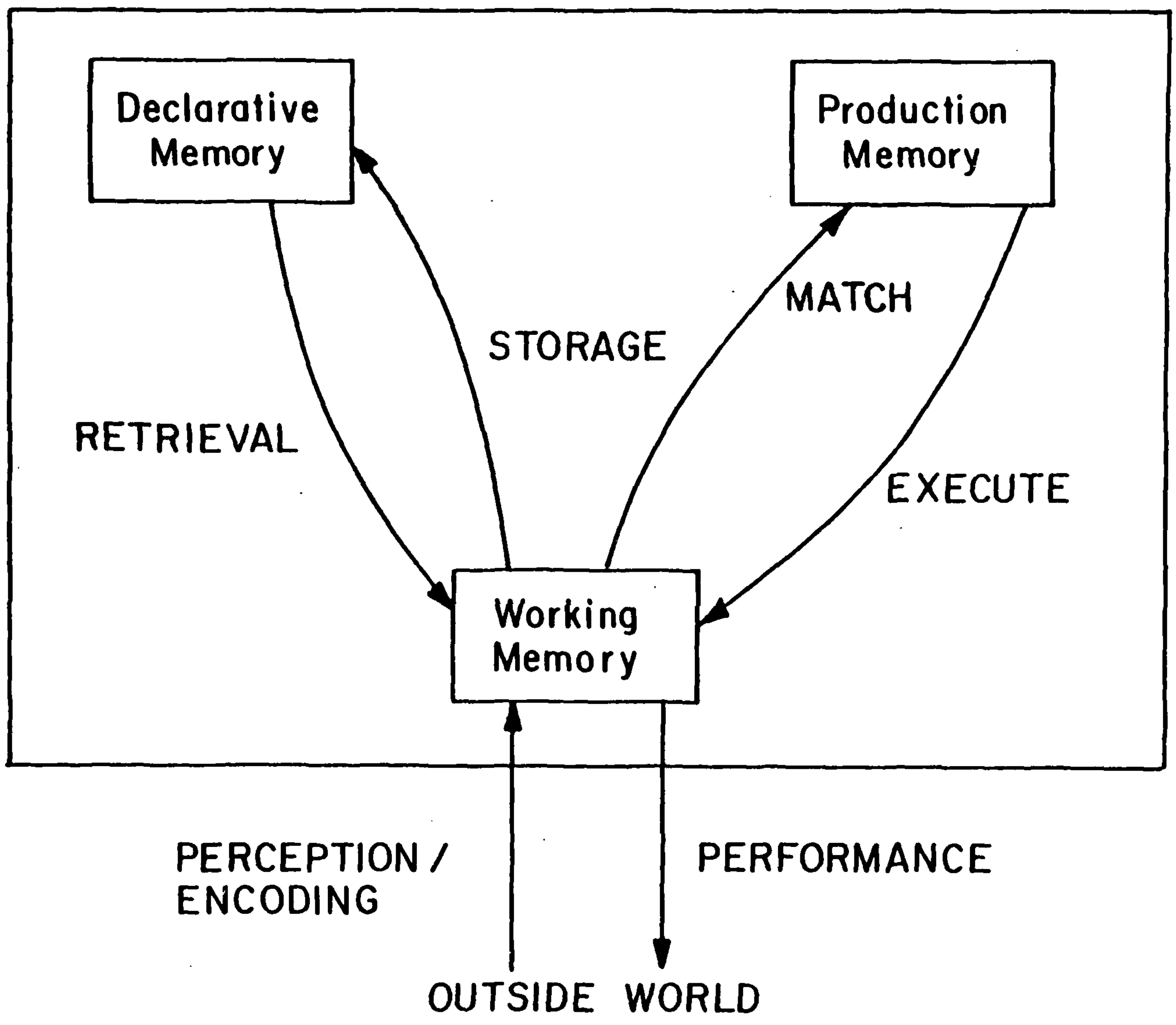
Declarative Memory
Production Memory
STORAGE
MATCH
RETRIEVAL
EXECUTE
Working Memory
PERCEPTION / ENCODING
PERFORMANCE
OUTSIDE WORLD

Fig. 1

different types of representations arise from different types of stimuli.

It is possible to store copies or encodings of working memory structures in long-term memory which later can be retrieved back into working memory. These long-term storage and retrieval processes also contribute to our understanding of the representation. We have to specify what the units are that are stored and what the units are that are retrieved. In specifying the retrieval and storage processes we define what the cognitive units (Anderson, 1980) are in our theory of knowledge representation.

Each production consists of a condition which is to be matched to the contents of working memory and an action which can be executed to add to the contents of working memory.[1] The similarity structure of the material is specified by the match process which decides what knowledge structures are similar enough to match to the same condition patterns.

Productions calculate transformation of working memory. That is, they match in their condition a set of cognitive units and specify in their action that new units be added to working memory. In the ACT framework, but not in all production system frameworks, these transformations are basically incremental. That is, the effect of a production is only to add new units to the system; it can never result in the deletion of units. Thus, the transformation computed by a production can be interpreted as mapping a set of cognitive units into a superset (the original units plus the additions). The one qualification to the incremental character of ACT productions is that they can add to an existing unit and so effectively modify it. So when a proposition is tagged as false it will no longer match to production conditions that it would previously have matched.

Many of the interesting transformations and responses that a production system can calculate depend on variable use. A variable is an element of a condition which can match to any element of working memory provided that the element appears in certain specified configurations and meets certain tests. In ACT we refer to these variables with terms prefixed by LV. Table 1 contains some examples of productions using variables to calculate transformations. The first production matches a rectangle in its condition. In so doing, the variables LVpoint1 and LVpoint2 are matched to the upper-left and lower-right corners of the rectangle. The

action of this production creates a diagonal connecting these corners. It is the use of the variables LVpoint1 and LVpoint2 which permit this transformation to be computed. Similarly, by use of variables the second production transforms a phrase of the form "friend of John" to "John's friend". The final production performs the inference that a parent's parent is a grandparent. The purpose of these productions is to illustrate the importance of variables in creating transformations of working memory structure. I have illustrated how productions might operate in a spatial array, a verbal string, and on a propositional structure. The fact that I have specified each production in English (my informal theoretical language for the moment) should not obscure that they may be operating on different representational types.

Insert Table 1 about here

It was argued in the previous section that a theory of different representation types would rest on the types of processes our system possessed for each type. I will argue that different representational types are matched differently in production conditions and have different production actions.

The Tri-Code Proposal[2]

The basic proposal in this paper is the human system has at least three types of knowledge representation which I will call temporal string, spatial image, and abstract proposition. The temporal string representation is used for representing objects in sequence such as words in a sentence. It might be considered an ordinal representation. The spatial image representation is appropriate for representing objects in spatial configurations. I use the term spatial rather than visual to make clear that this representational system is not tied to the visual modality. Both of these representations are *analog* in the sense that they try to preserve in their structure some of the physical structure of what they are representing. The abstract proposition, on the other hand, attempts to represent in its structure the semantically-significant connections in what is to be encoded. While it is easiest to specify these three representational types in terms of the information they tend to encode, this is not their fundamental distinction. It is always possible to contrive some way to represent any information in any representation. The fundamental differences among the representations lie in the different processes that use them.

Table 1
Three productions illustrating the use of variables to create transformations of data elements

P1:	IF	LV object is a rectangle
		and LVpoint1 is the upper left corner of LVobject
		and LVpoint2 is the lower right corner of LVobject
	THEN	create LVdiagonal with endpoints LVpoint1 and LVpoint2
P2:	IF	LVphrase has structure "LVnoun1 of LVnoun2"
	THEN	create LVphrase1 with structure "LVnoun2's LVnoun1"
P3:	IF	LVperson1 is parent of LVperson2
		and LVperson2 is parent of LVperson3
	THEN	LVperson1 is grandparent of LVperson3

To propose three or more representations is an obvious violation of standards of parsimony that have been prevalent in discussions of representation. One of the supposedly strong arguments (e.g. Anderson & Bower, 1973) for the propositional theory over the dual-code theory of representation (Paivio, 1971) had been its parsimony. However, these standards of parsimony reflect a too-narrow view of the phenomena to be explained. If we take as our goal to explain how a system evolves and develops to become intelligent and adaptive, then it would be very peculiar indeed if it did not have multiple representational types with different types tuned to different needs. It would take a rather complex set of assumptions to explain why there were not multiple representations.

Human cognition has to meet some very different demands. It has to process the ordinal structure of language; it has to analyze the spatial relationships of the environment; and it has to capitalize on the predictive character of the world permitted because of causal and inferential relationships. These are very different problems and it would be very poor design to have all these needs met by a single representational scheme rather than by multiple, different schemes that were optimized to deal with different aspects of the environment. To take a natural analogy, it would be as if the human digestive system used a single digestive substance for processing everything that was ingested. An artificial analogy comes from the LISP programming language. Initially, it was constructed with a very Spartan scheme for data representation that was designed to optimize certain kinds of symbolic processing. Since that time it has proven necessary to augment that language with facilities for array and string processing so that efficient performance could be achieved in various applications.

I do not mean to imply that we have only three representational schemes but I think good cases can be made for at least these three. Of course, what I really mean to denote by these representational systems are the three different types of processes that operate upon the three different representations. Therefore, the argument will be that the three types of representations bring with them processes that are well-suited for various applications. Such observations of adaptive value, in themselves, are strong evidence for the existence of these three representations. But, in addition, there is a considerable amount of empirical evidence pointing to each representation-process system.

Table 2 provides an organizational structure for the points to be made about the three representations. Table 2 has the three representational types crossed with the five basic production system processes -- encoding of external information into a working memory format, storage of information into the long-term declarative memory, retrieval from declarative memory, the match process by which information in working memory selects productions for application, and the construction of new structures in working memory through production execution. In each cell I have listed some of the properties of each process-by-type combination. I make no claim that Table 2 nor this paper exhaustedly lists all the processes that operate on any representational type. However, enough processes have been enumerated to justify the claim of distinct types. That is, each of these three representational types has processes defined on it with properties unlike those of the processes defined on any other data type. The next major sections will work through each data type justifying the claims made about the processes that operate on it.

Insert Table 2 about here.

Note, however, that the three data types are not distinguished with respect to the storage and retrieval processes for declarative memory. The final section of this paper will consider further the character of declarative memory and see what the consequences are of not distinguishing between these data types in declarative memory.

According to this analysis the case for distinct representational types is going to be made with respect to the <u>kinds</u> of encoding, match, and execution processes. Note the argument is not, for instance, that a match process is defined for one representational type and not for others. A production system could not function if that were the case. Rather, the argument is that different match processes are defined for different types. The evidence for this will come from the fact that the match process has different characteristics when applied to different representational types.

Temporal String Representation

Table 2
Summary of the Three Representations and Their Properties

	Temporal String	Spatial Image	Abstract Proposition
(1)Encoding Process	Preserves temporal sequence	Preserves configural information	Preserves semantic relations
(2)Storage Process	All-or-none of phrase units	All-or-none of image units	All-or-none of propositions
(3)Retrieval Process	All-or-none of phrase units	All-or-none of image units	All-or-none of propositions,
(4)Match Process			
(a)Degree of Match	End-anchored at the beginning	Function of distance and configurations	Function of set overlap
(b)Emergent Patterns	Ordering of any two elements, next element	Distance, direction, and overlap	Degree of Connectivity
(5)Execution: Construction of new structures	Combination of objects into linear strings, insertion	Synthesis of existing images, rotation	Insertion of objects into relational slots, filling in of missing slots

Encoding

The encoding process creates strings to record the sequential structure of events. It is a non-trivial question just how stimuli are segmented into event-units, but assuming this segmentation, it is a constraint on the encoding processes that they preserve the ordinal structure of events. A very important use of temporal strings is to encode word or morpheme order in language. I (Anderson & Paulson, 1977) have used the term verbal strings to refer to temporal strings encoding word order.

A significant aspect of the encoding process is that it encodes ordinal but not interval information about the event units. So, in a very important sense it is an abstraction from the event being encoded. It can be of great advantage in processing language that only ordinal language information is recorded (at least once the morphemes have been identified). The difficulty in converting speech into segmented units (Gill, Goldman, Reddy & Yegnanarayana, 1978) is testimony to the fact that one would not want to continue to process the speech signal as an interval structure. The fact that most rules of language interpretation (after phoneme identification) make only minimal reference to exact temporal properties is perhaps motivated by the difficulty of processing the exact temporal structure of a sequence spaced out over time. Similarly, inferring the causal structure of an event sequence is critically dependent on the ordinal structure but often is not ~~critically~~ dependent on the interval structure. This is not to say that events like pauses cannot be significant, but when they do occur they become another element, a pause, in the event sequence. Pauses can also be important in determining the hierarchical structure of an ambiguous stimulus (e.g., Bower & Springston, 1970).

Further evidence for the belief that temporal strings encode only interval information is the poor quality of human judgment about absolute time. This encoding scheme is in correspondence with a theory of time perception (Ornstein, 1969) which holds that passage of time is related to number of intervening events (or units in a string representation). This is not to say that we absolutely cannot perceive or remember interval properties of a time sequence; rather, the assertion is that such properties are not directly encoded in the temporal string. Such information can optionally be encoded as attributes of the ordered elements (e.g., "the goal was scored at 2:03 of the second period").

Long sequences of events are not encoded as single-level linear structures but rather as hierarchies of strings within strings. This is frequently referred to as phrase structuring where a phrase refers to the units in a level of the hierarchy. A phrase typically contains five or less elements. The idea of such hierarchical organization for temporal strings with a limited number of elements at any level has been proposed by many researchers (e.g., Broadbent, 1975; Johnson, 1970; Lee & Estes, 1981; Wickelgren, 1979). These phrase structures are often indicated by pause structures in serial recall.

Propositional vs. String Representation

One of the standard arguments for a propositional system over a multi-code system (e.g., Pylyshyn, 1973; Anderson & Bower, 1973) has been that the propositional code is sufficient to encode all kinds of information. It is particularly obvious how string information can be propositionalized and much of our research on language processing (Anderson, Kline, & Lewis, 1977) has worked with propositional encodings of sentence word order. Figure 2 shows the propositional network representation adapted from Anderson (1976) for "the tall young man". The reader is undoubtedly struck by the complexity of this representation relative to the simplicity of the string to be represented. The reason for the complexity is that one has to use conventions that are optimized for representing the complexities of other knowledge structures and cannot capitalize on the peculiar properties of the simple knowledge to be represented. The problem is not just one of awkward notation. There is considerable inefficiency in processing because the processes must also consider the needless detail. I think this example illustrates the efficiencies to be gained by permitting different representational types.

Insert Figures 2 and 3 about here.

Figure 3 shows a possible network notation for the string encoding of (the tall young man). In addition to representing the ordinal information, I have represented how other information would be encoded about the elements of the string. For instance, I have represented the fact that tall was pronounced without articulating the L and that young was stressed. It is because of the need to represent particular information about these instantiations of the word that one needs a type-token distinction. That is, it is not the word young in general

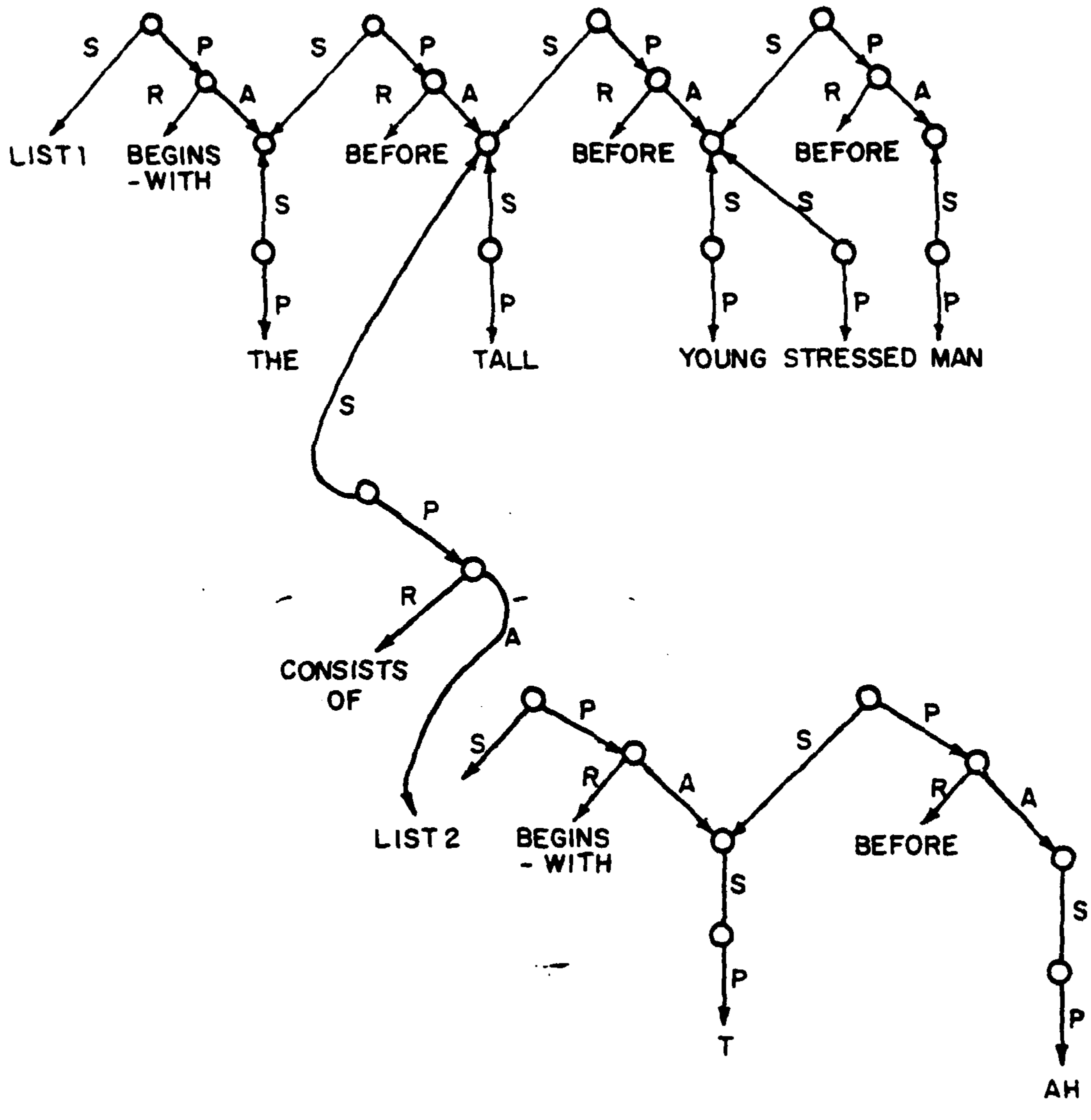
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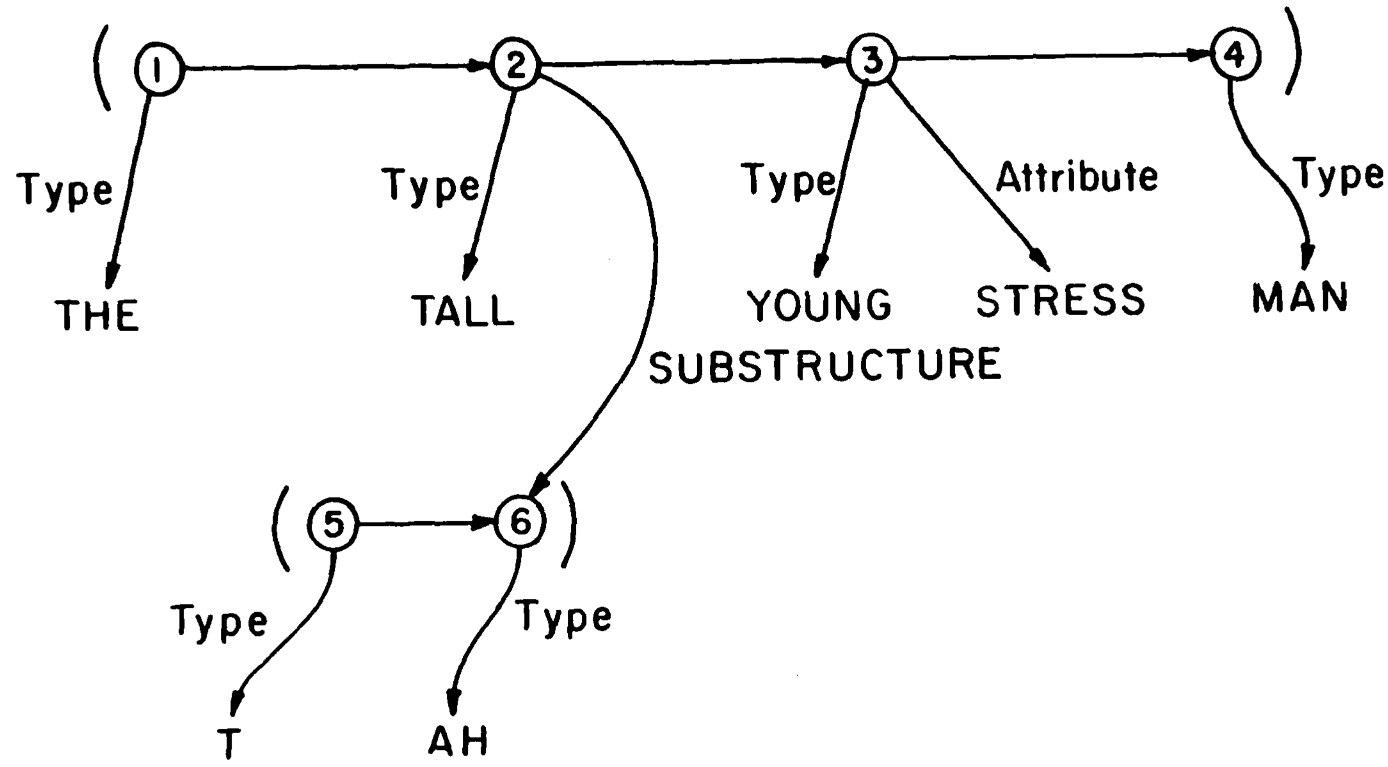
Fig 2



1
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TALL
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SUBSTRUCTURE
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Fig. 3

that is stressed, but rather this token of it. When one needs to be explicit about the type-token distinction, it is useful to use a network notation. In Figure 3, individual nodes represent the word tokens which point to the words by type links. Also illustrated here are attribute links (to indicate token 3 is stressed) and a substructure link to indicate the contents of token 2. Thus, in addition to the string structure, we need to have conventions to represent category information (i.e. the types for the tokens), attribute information, and substructure information. It will turn out that we will need similar category, attribute, and substructure embellishments for the image and propositional representations. Thus, it would be too simplistic to think one could represent a string by four elements. Still the notation is much more compact than Figure 2. Where Figure 2 had 42 links Figure 3 has 13. This notational difference is significant because it implies a corresponding difference in the complexity of the processing.

Image vs. String Representations If one cannot subsume string information under propositional encodings, a natural tendency is to try to subsume it under spatial information. One might try to reduce temporal strings to one dimensional spaces. However, it should be clear that they are not spatial structures because they do not encode interval information and spatial structures do. The significance of the omission of interval information will become clear when we consider the <u>next</u> and <u>insert</u> operations that can only be defined on ordinal structures, not on interval structures.

There has been a considerable history of comparing temporal versus spatial encodings of sequential structure (R. Anderson, 1976; Healy, 1975,1977; Hitch, 1974; Mandier & Anderson, 1971) and it has not been supportive of the idea that spatial and temporal encodings are the same. Generally, temporal encodings are superior for encoding order. Significantly, R. Anderson (1976) found the superiority of temporal encodings greater for words than pictures. Healy (1975) found phonemic encoding only for temporal presentation. Mandler & Anderson (1971) argue that when temporal and spatial presentation is confounded, subjects set up two independent and additive codes. In sum, it seems very improbable that one will be successful in trying to argue that a temporal code is just a degenerate case of a spatial code.

Insert Figure 3 about here.

Storage and Retrieval

Temporal strings are stored in long-term memory according to their phrase units and they are retrieved in phrase units. The work of Johnson (1970) has nicely documented the memorial consequences of this hierarchical phrase structure. By various spacing techniques he was able to control the phrase structure of arbitrary strings of letters. He found high conditional recall probabilities across phrase boundaries such that once into a unit, recall of one member was very predictive of recall of another. However, in transitions across boundaries there was much less predictability in recall.

The phrase structure units of temporal strings appear to be instances of what I (Anderson, 1980) have called cognitive units. Cognitive units are encoded into long-term memory in an all-or-none manner and are similarly retrieved. This means that all the elements of a phrase structure unit will be recalled or none will be recalled. This would certainly impose the high conditional recall probabilities noted by Johnson. However, it does predict a stronger within-phrase contingency than found by Johnson -- essentially, recall of one element should imply perfect recall of all other members. In fact, various complications can serve to degrade all-or-none recall to some-or-none recall as found by Johnson. This will be discussed later in this article after further assumptions about representation have been established.

Pattern Matching: Degree of Match

Much of the distinctive character of temporal strings becomes apparent when we consider the processes by which temporal patterns are matched. In the production system framework this comes down to issues of how production conditions are matched to data that is in working memory. An interesting situation occurs when the system has to process some data that partially matches a well-known pattern. There are strong asymmetries in speed and success of recognition. One of the strongest effects has to do with the importance given to the beginning of the string. Thus, "JVLV" is much better for calling to mind "JVLVB" than is "VLVB". This property of temporal strings was capitalized upon in the research of Tversky and Kahneman (1974) who found subjects thought more words began with K than had K in the third position. Apparently, it is easier to find patterns which match K---- than which match --K--.

A New Experiment. We have recently completed in our laboratory a relatively systematic investigation of the sequential dependencies that exist in matching strings of letters. We had subjects commit to memory 10 paired-associates consisting of four-consonant strings paired with a digit from 0-9 (e.g., XRDT-7). Each digit was used once. Over the 10 consonant quadragrams, each of twenty consonants (Y was excluded) occurred twice. The material was also designed so that each pair of consonants occurred uniquely in a single quadragram. In the initial learning phase, subjects were asked to recall digit to quadragram (XRDT-?) and quadragram in correct order to digit (? -> 7). They were drilled in this manner until they had made each type of recall to each pair successfully four times.

Subjects were then transferred to the reaction time phase of the experiment in which they saw two, three, or four letters and had to indicate what string this was by pressing the appropriate digit. The letters could occur in any order. From a given string there were 24 possible distinct 4-letter probes, 24 3-letter probes, and 12 2-letter probes. Over the course of the reaction time phase subjects judged every possible probe for the 10 original quadragrams--for 600 trials in all. So, for instance, included among the 60 probes for the above pair would be RXDT ->, XTR ->, and DR ->.

We were mainly interested in the speed with which the subjects could recognize these transformed letter strings and recall the digit. Undoubtedly, they would be relatively fast for the strings that reproduced what they studied (i.e. XRDT->), but the question was what other patterns would serve to quickly retrieve the string from memory. This would tell us something about the properties of the production pattern matcher. To be explicit, we assumed that the response of the subject was governed by productions on the order:

```
     IF the probe is the string (LVA LVB LVC LVD)
        and LVA, LVB, LVC, and LVD are associated to response LV#
THEN press LV#
```

The critical issue concerns how the second clause in the condition is matched. Our hypothesis was that there would be a substantial front-anchoring effect. That is, if the first letter in the probe (LVA) matched the first letter of a stored string, subjects would be fast independent of order in the rest of the probe. However, we went into the experiment with fairly open minds about what we would find. By using all possible orders and all possible subsets, we tried to assure we would be able to detect any trend in the data.

Table 3 presents the data from the experiment classified according to the position of the first two letters in the original string studied and according to length of string. So, for instance, if XRDT had been the original study string, the probe DXT- would be as a 3-tuple whose first letter occurred in position 3 of the original string and whose second letter occurred in position 1. There was little effect of the study positions of the third and fourth letters on judgment time to 3-tuples and 4-tuples which is why I have averaged over that factor. Subjects are nonetheless faster and more accurate to 3-tuples and 4-tuples than 2-tuples. This is interesting in its own right but for current purposes the interesting phenomena concerns how judgment time varied as a function of first and second letters. Subjects are clearly faster when the first letter of the test string was the first letter of the study string. They were also somewhat faster in the first letter match condition if the second letters of test and study strings also matched. Subjects were somewhat worse when the first test letter was taken from the fourth position than when it was taken from second or third study positions. Outside of this there seems no other systematic effects. Thus, this experiment does nicely demonstrate the strong front anchoring and order dependence in matching strings. Somewhat similar results have been reported by Angiolilio-Bent & Rips (1981).

Insert Table 3 about here.

Angiolilio-Bent & Rips (1981) propose that the important variable is distance the letter in the probe is removed from its position in the target. This explains the front-anchoring effect but also predicts numerous effects that do not obtain in our data. One such prediction is that there should be an end-anchoring effect for four-tuples as large and the front anchoring effect. The best way to test this is to contrast 4-element probes that are identical in first two positions but differ as to whether they end with the last letter of the study string and to contrast probes that are identical as to last two position but differ as to whether they begin with the first letter of the study string. The first contrast tests for end-anchoring. The difference between end-anchored and not-end-anchored probes is 1.62 vs. 1.68 sec. The second contrast tests for front anchoring. The difference between front-anchored and not-front-anchored probes is 1.57 vs. 1.74 sec. Thus, while there may be some end-anchoring effect, the front-anchoring effect is nearly three times as large. Angiolillo-Bent & Rips data can similarly be analyzed to show a stronger front-anchoring effect but the contrast is not as sharp.

Table 3
Mean Reaction Times in Seconds and Error Rates (in parenthesis) for the String Naming Experiment

Location of First Letter	Location of Second Letter	2-tuples	3-tuples	4-tuples	Mean
		1.77	1.62	1.55	1.65
1	2	(.08)	(.06)	(.05)	(.06)
		2.18	1.67	1.56	1.80
1	3	(.13)	(.04)	(.03)	(.07)
		2.21	1.78	1.61	1.87
1	4	(.09)	(.07)	(.05)	(.07)
		2.46	1.93	1.66	2.02
2	1	(.15)	(.08)	(.03)	(.09)
		2.49	1.89	1.71	2.03
2	3	(.14)	(.04)	(.05)	(.08)
		2.63	1.90	1.72	2.08
2	4	(.12)	(.09)	(.05)	(.09)
		2.60	1.85	1.75	2.07
3	1	(.12)	(.07)	(.06)	(.08)
		2.48	1.84	1.68	2.00
3	2	(.11)	(.07)	(.04)	(.07)
		2.20	1.92	1.64	1.92
3	4	(.12)	(.09)	(.04)	(.08)
		2.65	2.05	1.80	2.17
4	1	(.17)	(.06)	(.06)	(.10)
		2.53	2.04	1.83	2.13
4	2	(.17)	(.07)	(.05)	(.10)
		2.49	1.98	1.76	2.08
4	3	(.19)	(.06)	(.06)	(.10)
		2.39	1.87	1.69	1.99
Mean		(.13)	(.07)	(.05)	(.08)

It should be noted that this analysis of string-matching has been purely descriptive. That is, I have simply noted the strong front-anchoring effect without proposing a mechanism. This is not to imply that it is not reasonable to attempt a mechanistic analysis of the phenomena as in Angiolillio-Bent and Rips. However, it is not essential for current purposes. The goal here is to show that string pattern-matching is sensitive to properties that image pattern-matching or proposition-pattern matching is not. Later sections will provide evidence that image and proposition matching do not show strong front-anchoring effects.

In the current enterprise, I have taken a mechanistic theoretical framework (i.e. the ACT production system) that is decomposed down to the level of descriptive properties of the string pattern-matcher. Like Angiolillio-Bent & Rips, one could try to decompose the mechanistic analyses fruther, but one does not avoid the need to assign descriptive properties to the primitives. In their case, they assume match time for an individual letter in a probe increases with displacement. Thus, they have decomposed a descriptive statement about string matching into a series of descriptive statements about letter matching.

Pattern Matching: Emergent Properties

Sometimes when we are trying to match a pattern against a data structure, the pattern completely specifies the data structure. Sometimes, however, the pattern is only testing for a certain property of the data structure which does not uniquely specify the data structure (or said differently, more than one data structure could have this same property). As a simple example concerning word spelling, contrast checking the complete spelling of a word versus just testing if it begins with the correct letter. Intuitively, it would seem easier to determine that "ILLUSTRATION" begins with I than that it is spelled correctly in all places. It might seem only "logical" that partial information can be matched more rapidly complete information, but often this is not the case. Consider two examples from spelling: First, it is harder to verify set information than sequence information although set information is just part of sequence. That is, it is hard to decide LINOSRTAU contins all the letters in ILLUSTRATION than to decide ILLUSTRATION matches both set and sequence information. Second, it is harder to verify that a word is spelled correctly in every second position than that a word is verified correctly in all positions. That is, it is hard to decide about the correctness of IXLXSXRXTXOX.

When it is easier to verify a partial property about a data structure than the full pattern specification, we have an instance of an emergent property. Some of the clearest differences among data types concern their emergent properties. Among the interesting emergent properties of temporal strings concerns the ability to judge the order of two elements from a string and the ability to retrieve the next element in a string. While these properties can be judged much more rapidly than the full string, it is not the case that either property is judged in constant time. There are important factors affecting the speed with which these judgments can be made and these factors serve to give strings further unique process characterization.

Retrieval of the Next Element. There is an obvious analogy between temporal strings and lists from programming languages. One of the features that characterize lists is the calculation of the next element. Most list implementations provide most rapid access to the front of the list and subsequent members are retrieved by chaining through a series of nexts. The same seems true of strings. Sternberg (1969) documents that for short strings the time to calculate the next element depends on the position of the item in the list with later items taking longer. When it comes to longer, hierarchically structured strings, the main factor is position within the subphrase (Klahr, Chase, & Lovelace, submitted). The next operation would appear to be a clear distinction between a string and a spatial image. Without a direction, the next element in a multi-dimensional spatial image is not specified but even with a direction specified, Kosslyn (1980) has shown that retrieving the next element a function of the physical distance between the objects.

Order Judgments. A frequent task is to judge the order of two elements from a string. This would be accomplished in a production system by the use of special match predicates for order. So, for instance, the following production would directly retrieve the answer to a question of whether A is before D in the string ABCDEF:

```
    IF asked whether LVX is before LVY
       and LVX is before LVY
  THEN respond yes
```

The second clause being matched in the condition "LVX is before LVY" requires direct access to information about order in the string. There has been a great deal of work on linear orderings (e.g., Potts, 1972, 1975; Trabasso & Riley, 1975) suggesting that such order information is emergent and that one does not have to

chain through the intermediate terms between A and D to determine their ordering (i.e., it is not implemented as a series of nexts). In these experiments subjects learn a linear ordering by studying a set of pairwise orderings--for instance, A is taller than B, B is taller than C, C is taller than D, D is taller than E, and E is taller than F. Despite the fact that subjects only commit to memory the adjacent pairings, judgments are easier to make the farther apart the elements are. These results are generally taken as evidence against a propositional encoding for linear order information. These judgments can be made over very long strings which require hierarchical encoding (Woocher, Glass, & Holyoak, 1978). One still gets the same distance effects. Thus, it seems the emergent information about ordering is not restricted to a single phrase level in the hierarchy; rather one can judge the order of any two elements in the hierarchy.

It should be noted here that I am not proposing a mechanism for the extraction of such linear ordering information. Again, I am just noting a property of the pattern-matcher which serves to distinguish treatment of strings from other knowledge representations. However, there is no shortage of proposals about how these linear ordering judgments might be performed. For a recent discussion of these proposals see Holyoak & Patterson (1981).

Construction of New Strings

Strings are not only created by encoding the order of events in the environment. They can also be created as the outcome of internal computation. Thus, we can create a string encoding all the primes under 20: (((1 2 3) (5 7)) ((11 13) (17 19))). This is modelled in a production system by production actions building new structures. There is nothing in such construction unique to strings. Similar structuring building operations apply to the other representational types. However, an important property of strings is the ability to modify an existing string by inserting or deleting an element. So, for instance, we can modify the string above by inserting a 0 after the 17.

The insertion operation strengthens the correspondence between strings and lists from computer science. It also shows another reason why it is adaptive that strings be ordinal rather than interval structures. The insertion operation is only uniquely defined if we have an ordinal structure. The ability to insert is critical in domains as disparate as transforming an English sentence to solving a detective mystery by inserting the

critical hypothetical event.

The complementary operation to inertion is deletion which again the human mind also has great facility with. This operation makes even clearer the distinction between temporal string and a spatial image. When we delete an event we do not create a string with a "hole".

It would seem an intriguing topic to consider what the characteristics are of strings formed by insertions and deletions. A considerable amount of experimental research has been concerned with whether subjects enjoy positive transfer between lists related by such transformations (for reviews see Murdock, 1974; Young, 1968). Unfortunately for current purposes, that research has confounded detecting such transformations with using them.

Purpose of Temporal Strings

To review, I have identified some of the properties that distinguish temporal strings from other knowledge representations. It is noteworthy that many of their unique properties are just what one would associate with lists in a programming language like LISP. Like lists, they encode order and not interval information and they show a strong primary effect in that they can only be accessed from the front. Like lists they seemed designed to permit access to the next element, and to permit insert and delete operations. The one property we considered which is unlike most list structures concerns emergent information about order. Also unlike lists it is possible to index the list from a member (e.g., what list does February occur in?). However, this double-linkage (from element to cognitive unit and from cognitive unit to element) is not something that distinguishes strings from other representational types.

Like list structures in programming language, temporal strings exist to facilitate certain types of common mental computations. They facilitate these computations because of the unique array of processes associated with them. If it was necessary to develop list-processing languages to facilitate progress in AI, we can be sure it was necessary for the human mind to evolve temporal strings to facilitate natural intelligence.

Spatial Image Representation

Encoding and Notation

Spatial images are structures that preserve the configuration of elements of a spatial array. My current best guess is that an image is isomorphic to the array up to a size transformation. That is, it encodes configural information but not absolute size. The experiment by Kubovy & Podgorny (1981) supports this claim. They presented their subjects with a pair of random polygons and had subjects judge whether they matched in shape. Same shape polygons could vary in the dimensions of size and rotation in the plane. They found a large effect of rotation on judgment but no effect at all of change in size. This is just what is predicted from the image representation proposed here. That is, the image preserves information about relative position and not absolute distance or size. Unfortunately, as Kubovy & Podgorny note, effects of size transformation have been found by other researchers. The experimental issue is tricky because size effects would be expected to whatever degree subjects were making their judgments in terms of position of the stimulus relative to a larger framework that did not increase with size of the stimulus. In this case, the overall configuration would change with size. Until the experimental issues are resolved, I can only say that the Kubovy & Podgorny results are the ones that should obtain in the right situations if the theory of imagery being presented here is correct.

The current proposal to have images preserve orientation and not size is based on my own intuitions about what is important about a spatial image and what I seem to preserve in my images. I need to recognize patterns under changes of size (e.g., different size print) and seemingly do so with ease. On the other hand, objects can change identity under rotation (e.g., a Z becomes an N; a square becomes a diamond) and I experience subjective difficulty in making matches that have to correct for rotation. However, it also needs to be stressed that no major claim in this pap~~r~~e rests on the ~~claim~~ assumption that images do not encode absolute size. Far from that, the tri-code proposal would be strengthened if it could be shown that images did code absolute size in their structure. It is fairly clear that absolute size is not encoded in temporal strings or abstract propositions.

A notation for expressing spatial images is somewhat awkward for scientific discourse and much of the

debate over image representation has really been motivated by this awkwardness in notation. Figure 4 presents possible encodings and various notations for their spatial images. We can use the actual stimulus (part a), but then we must realize that only the position of the objects and not their exact visual detail is to be taken seriously. Because of working memory limitations one could not encode all the details of all three objects *in a single image*. If the visual detail is encoded it must be done by means of subimages. It is ambiguous in Part (a) whether the detail of the objects is encoded at all. Parts (b) and (c) of Figure 4 illustrate that ambiguity. In both figures we just have letters in the array which are tokens for the parts, but in part (b) these tokens point to subimages that encode the visual detail while in part (c) there are only categorical descriptors. In part (b) each of these subimages would have an encoding as to their subparts. The full encoding in part (b) including subimages allows judgments such as whether the triangles are equilateral. Part (d) of Figure 4 gives an alternate encoding of part (c) in which the array is reduced to coordinate information. Part (e) shows a loose English rendition of the image information. I do not want to prescribe the correct notation here, but rather simply want to suggest that choice of notation depends on purposes. Clearly, one needs a notation that encodes saliently the information being used by the processes operating on the representation. So, if one is concerned with processes that operate in the position of subelements then (d), where that information is explicit, is to be preferred to (c) where it is implicit. Whatever the choice of notation, it should not obscure what the image really is -- information about the spatial configuration of a set of elements.

Insert Figure 4 about here

Parts (b) and (c) illustrate the use of categorical and substructure information that we already saw with respect to string representations. Note it is possible to use this substructure representation to embed images within images to arbitrary depth. Thus, an important part of this proposal is that images can have a hierarchical character. It is also possible to have attribute information when, for instance, we represent the color of an object in an array. Also, size information could be stored with an image as an attribute.

It is important at times to have the ability to embed a token within an image. The structure of the token

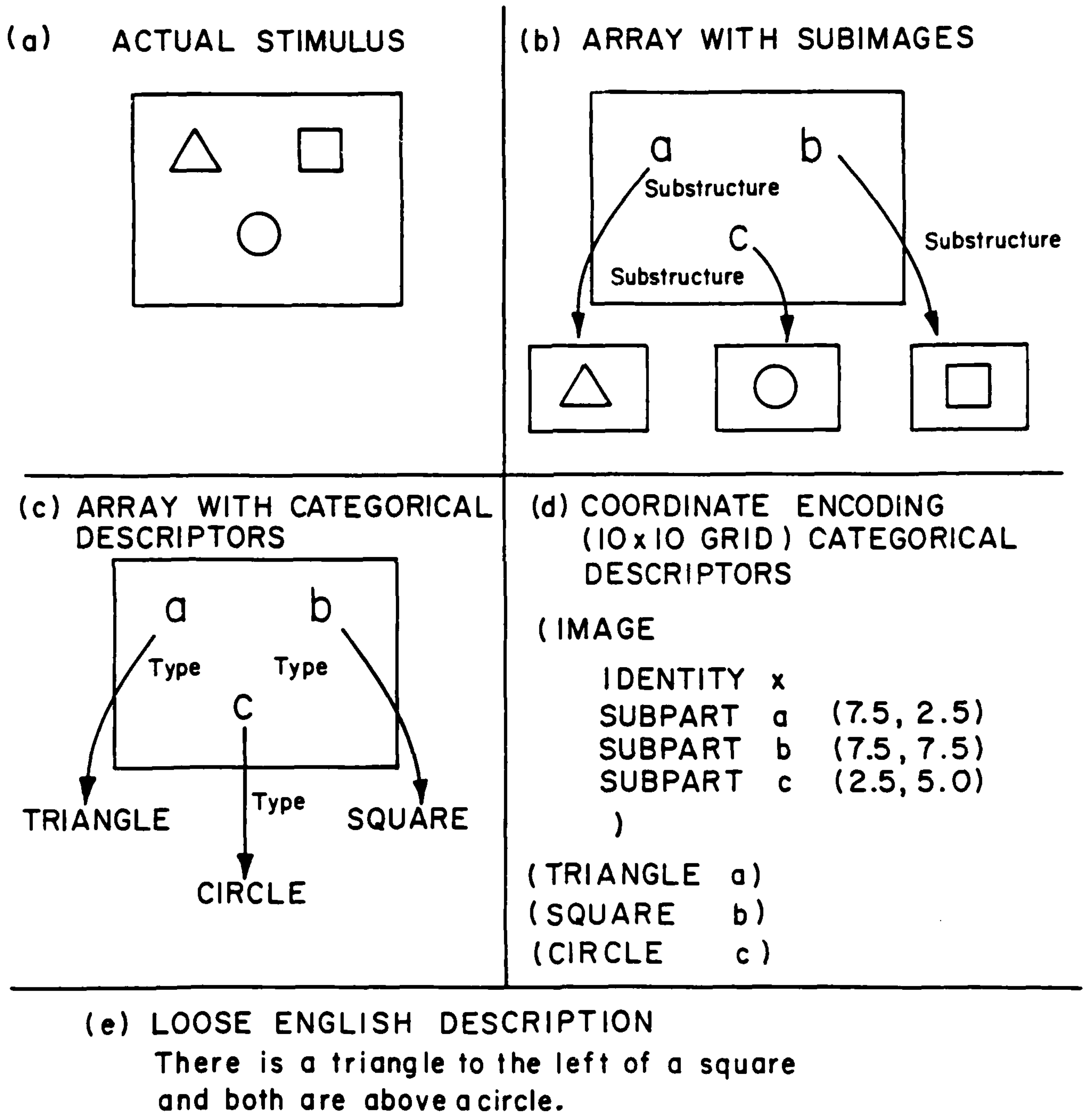

(a) ACTUAL STIMULUS
(b) ARRAY WITH SUBIMAGES
a
b
c
Substructure
Substructure
Substructure
(c) ARRAY WITH CATEGORICAL DESCRIPTORS
a
b
c
Type
Type
Type
TRIANGLE
SQUARE
CIRCLE
(d) COORDINATE ENCODING (10 x 10 GRID) CATEGORICAL DESCRIPTORS
(IMAGE
IDENTITY x
SUBPART a (7.5, 2.5)
SUBPART b (7.5, 7.5)
SUBPART c (2.5, 5.0)
)
(TRIANGLE a)
(SQUARE b)
(CIRCLE c)
(e) LOOSE ENGLISH DESCRIPTION
There is a triangle to the left of a square and both are above a circle.

Fig. 4

can be unpacked by other images and/or propositions. The spatial image is under the same capacity limitations imposed by working memory as are temporal strings. That is, in a single image unit it is possible to encode the relative positions of a limited number (definitely less than 7) of objects. One consequence of embedding tokens in an image is that it is possible to have very accurate information about the spatial configuration of the objects in a scene with very little information about the configural properties of the objects themselves. This is an important way that these spatial images differ from true pictures. Of course, this possibility sits well with most people's experiences of imagery -- for instance, the notorious zebra without stripes (Bower, 1972) or Pylyshyn's (1973) image of a room scene. It also is in accord with results such as those of Navon (1977) that one can identify the configural properties of a structure before the components.

So, in Bower's example, we might represent the zebra in terms of the relative position of head, legs, body, and perhaps a stripe or two without specifying all the stripes. In Pylyshyn's example we may specify the location of the lamp in the room and of other furniture, without specifying the details of the furniture. In these cases it is possible (optional) to have more detailed information in a subimage pointed to from the whole image--a subimage of the face with stripe information or of the lamp. In accord with Navon, however, it will take longer to retrieve the detail because the subimage must be retrieved from the whole image.

This hierarchical representation of the image is basically in accord with other hierarchical proposals such as that of Marr & Nishihara (1978) or Hinton (1979). These proposals differ from the current one basically in pursuing technical issues to levels of detail not important to the points to be made here.

Kosslyn (1980) has made a distinction between propositional representations and quasi-pictorial representations for images. His book presents a detailed development of a quasi-pictorial theory. It is clear that what is being proposed here (as, indeed, what is proposed by Marr & Nishihara or by Hinton) is a hybrid by Kosslyn's classification. Like a propositional representation, this has a clear structure with relations (the spatial configurations) and arguments (the elements). Like a quasi-pictorial representation, it preserves information about shape and has a non-arbitrary relation to the object represented. Unlike a proposition, it has in no clear sense syntax or truth value. Unlike an image, it does not have size as an inherent property.

Given the overall purpose of this paper, it would clearly be a digression to get into a point-by-point, experiment-by-experiment accounting of why this hybrid model is to preferred to a pure propositional or a pure quasi-pictorial. Some of the evidence is discussed here and other evidence is reviewed in sources like Anderson (1980a) or Hinton (1979). In most general terms, images have been shown to have both strong structural and strong quantitative properties. Hybrid proposals such as this are efforts to acknowledge this. In fact, Kosslyn tries to deal with the structural properties of images by proposing auxiliary propositional representations and distinguishing between skeletal vs. elaborated images. Most important for current purposes, however, is that this hybrid representation identifies process-properties of images which have no correspondence in the other two representations.

The encoding process involves a faithful representation of the spatial relationship of objects in the environment up to transformations of scale. As in the case with temporal strings, a rather sophisticated pattern recognition process is being assumed for object segmentation. Thus, an image of a scene is in no way a point-by-point representation of the scene (unless the scene only consists of a few dots). For instance, the objects in an image of a square might consist of the lines and corners where the lines and corners are the elements whose relative spatial location is represented but whose visual detail is not unpacked in the image. Imaging the above mentioned square would require maintaining eight objects (four sides, four corners) in working memory. This might exceed the capacity of working memory. Phenomenally, I have considerable difficulty in holding a square in working memory with its four sides and four corners. It is my experience that I can only hold in my "mind's eye" some parts or aspects of the image in sharp focus, but that other components can be quickly produced upon demand.

The Santa Study. The basic claim is that images encode information about a spatial configuration whereas strings do not. By spatial configuration I mean to denote both multiple dimensions and ordinal information about inter-element differences. Both of these are lost in the sequential structure of a string. The study by Santa (1977) nicely illustrates this basic difference between matching of images and temporal strings. The two conditions of Santa's experiments are illustrated in Figure 5. In the geometric condition (part A of Figure 5), subjects studied a spatial array of three geometric objects, two geometric objects above and one below. As the

figure shows, this array had a facelike property--without much effort one can see eyes and a mouth. After subjects studied it, this array was removed and subjects were immediately presented with one of a number of test arrays. Various possible test arrays, given the study array, are illustrated in Figure 5A. The subjects' task was to verify that the test array contained the same elements, though not necessarily in the same spatial configuration, as the study array. Thus, subjects, having seen the study array, should respond positively to the first two arrays in Figure 5A and negatively to the other two arrays. Interest was focused on the contrast between the two positive test arrays. (There were other positive test arrays, not illustrated, that presented the three items in different orders). The first array is identical to the study array, but in the second array the elements are arrayed linearly. Santa predicted that subjects would make a positive judgment more quickly in the first case where the configuration was identical, since, he hypothesized, the visual memory for the study stimulus would preserve spatial information. The results for the geometric condition are displayed in Figure 6. As can be seen, Santa's predictions were confirmed. Subjects were faster when the geometric test array preserved the configuration information in the study array.

Insert Figures 5 & 6 about here.

The results from the geometric condition are more impressive when they are contrasted with the results from the verbal condition, illustrated in Figure 5B. Here subjects studied words arranged in spatial configurations identical with geometric objects in the geometric condition. However, because it involved words, the study stimulus did not suggest a face or have any pictorial properties. Santa speculated that subjects would encode the word array into a string according to normal reading order--that is, left to right and top to bottom. So, given the study array in Figure 5B, subjects would encode it "triangle, circle, square." Following the study stimulus, one of the test stimuli was presented. Subjects had to judge whether the words in the test stimulus were identical with those in the study stimulus. All the test stimuli involved words, but otherwise they presented the same possibilities as the tests in the geometric condition. In particular, the two positive stimuli exhibited a same configuration and a linear configuration, respectively. Note that the order in the linear array is the same as the order in which Santa predicted subjects would encode the study stimulus. Santa predicted that, since subjects had encoded the words linearly from the study array, they would be fastest

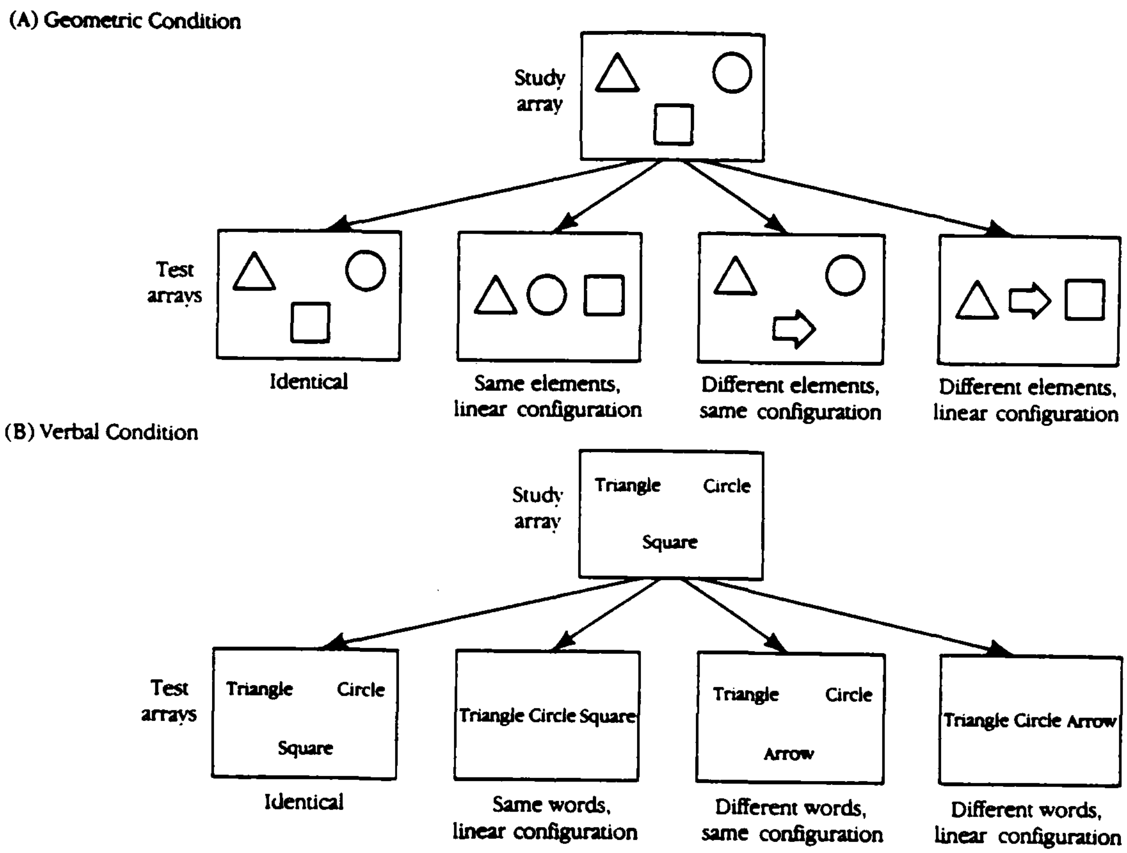

(A) Geometric Condition
Study array
Test arrays
Identical
Same elements, linear configuration
Different elements, same configuration
Different elements, linear configuration
(B) Verbal Condition
Study array
Triangle
Circle
Square
Test arrays
Triangle
Circle
Square
Triangle Circle Square
Triangle
Circle
Arrow
Triangle Circle Arrow
Identical
Same words, linear configuration
Different words, same configuration
Different words, linear configuration

Fig. 5

when the test array was linear. As Figure 6 illustrates, his predictions were again confirmed. The verbal and the geometric conditions display a sharp interaction.

Storage and Retrieval

According to the theory presented here, these image units should be stored and retrieved in the same all-or-none manner that is true of string phrases. This means that if we looked at image recall, we could see the same chunking that Johnson (1970) observed in his research. To my knowledge, such research has yet to be done except in the domain of chess and go (Chase & Simon, 1973; Reitman, 1976) where this basic prediction has been confirmed.

Pattern Matching: Emergent Properties

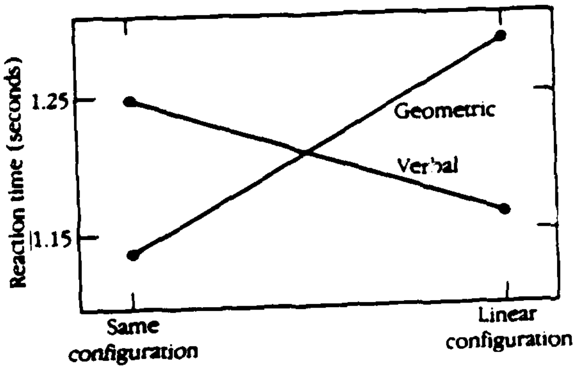
It has been frequently noted (Kosslyn & Pomerantz, 1977; Paivio, 1977) that spatial images appear to bring with them a host of emergent properties. Just as it was possible to directly test for the order of two objects in a temporal string, so it appears possible to directly test in an image for the distance between two objects, direction between two objects, and whether two objects overlap.

An example by Simon (1978) illustrates the emergent property of overlap judgment:

> Imagine but do not draw a rectangle 2 inches wide and 1 inch high, with a vertical line cutting it into two 1-inch squares. Imagine a diagonal from the upper left-hand corner to the lower right-hand corner of the 2 X 1-inch rectangle. We will call this line diagonal A. Imagine a second diagonal from the upper right-hand corner to the lower left-hand corner of the right *square*. Do the two diagonals cross?

The answer to this question appears to be immediately available.

Another emergent property of an image is the ability to make judgments about the relative position of two objects. For instance, Maki (1981), Maki, Maki, & Marsh (1977) have looked at subject ability to make north-south or east-west judgments about the position of cities on a map. This is like the work on judging ordering in linear arrays which I attributed to a string representation. Like the work on linear orderings these judgments are faster the further two cities are apart. However, there appears to be an important difference. Judgments of distance appear to be affected by the hierarchical structure of the picture. Thus, distance effects



Reaction time (seconds)
1.25
1.15
Geometric
Verbal
Same configuration
Linear configuration

Fig. 6

disappear for pairs of cities that cross state boundaries (Maki, 1981). Stevens and Coupe (1978) have shown that these judgments can be severely distorted due to the hierarchical character of image representation. For instance, they documented the frequent misconception that Reno is east of San Diego. This derives from the fact that Nevada is east of California and the location of the cities is represented with respect to these states. On the other hand, judgments of linear ordering seem unaffected by attempts to impose a hierarchical structure (Woocher, Glass, & Holyoak, 1978).

Pattern Matching: Degree of Match

The Santa study illustrated that rate of matching is affected by the spatial configuration of a series of objects. It is also affected by the interval properties of the figure. Speed of pattern matching seems to be a continuous function of the degree of distortion between the pattern configuration and the data to be matched (Posner & Keele, 1970). This is something quite unlike what is seen with matching of strings or with matching of propositions.

Another unique feature of image pattern matching is that a data structure can be matched to a pattern solely on the basis of a match in the configuration of its elements even when the elements themselves do not at all match the pattern. So, for instance, without trying we see the structure in Figure 7 (adapted from Palmer, 1975) as a face. This contrasts sharply with temporal strings where it is unlikely that one string of elements will evoke recognition of a completely different string. Of course, one-dimensional strings without interval structure do not permit the same variety of configural properties as do images and so lack much of the uniqueness of an image configuration.

Insert Figure 7 about here.

Image Construction

As with strings, we can synthesize new images by combining old ones--for instance, we can imagine a triangle on top of a square, our friend on an elephant, or a line between two points. In each of these cases, the larger image is constructed by specifying the location of one subimage relative to the other--for example, we might specify that the bottom line of the triangle be identical with the top line of the square. Images so

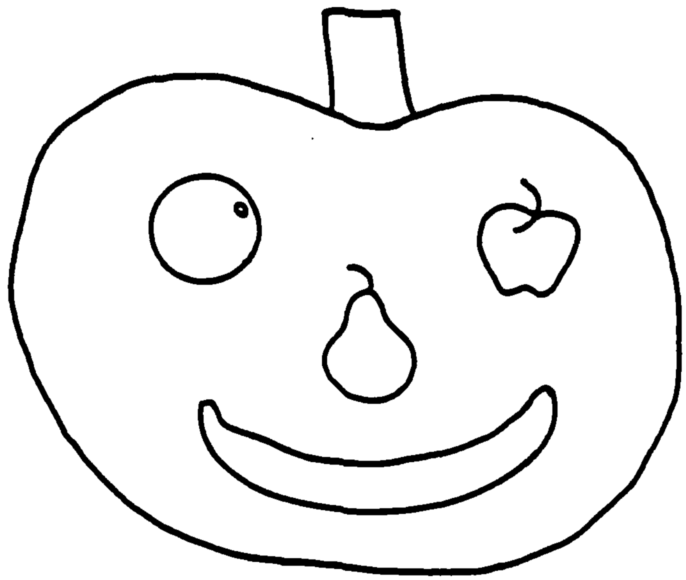


Fig. 7

constructed have the same hierarchical character as phrase units constructed out of sub-phrases.

The hierarchical character of a synthesized description may not correspond to the description that would have been derived had the synthesized object been directly perceived. This is because the hierarchical organization produced by direct perception can be different than that forced by synthesis. This is illustrated by the synthesis problems in Figure 8. In each case it is difficult to identify the object formed by the synthesis. For instance, part (b) is hard to perceive because separate line segments in the parts become single lines in the whole. This informal example agrees with the more careful studies of Palmer (1977) who showed that the ease of recognizing synthesized objects depends critically on whether the subunits to be synthesized correspond to the units the whole object would naturally be segmented into. Thus, the image representational system allows different descriptions for the same object.

Insert Figure 8 about here.

In this framework, image rotation becomes a special case of image construction. A new image can be constructed as a small rotation of another. The sort of production that performs rotation would match the to-be-rotated image in its condition and performed the rotation in its action. It would create a new image in working memory slightly rotated. Iterative application of this production would achieve further rotation. I infer from the literature on rotation that images can only be rotated small amounts at a time. Note that this feature indicates that the image is a distinct representational type in that small incremental rotation only applies to images, but the feature says nothing about the correct notation for describing images.

A Production System for Mental Rotation. Because of the important position of the research on mental rotation in discussions of imagery and because it is frequently thought that production systems and imagery processes are incompatible, it would be useful to display a production system that is actually capable of simulating the Shepard and Metzler (1971) task. This production system will have the further advantage of showing how different types of representation can be coordinated within one set of productions--indeed, within one production. This production system will borrow heavily from the proposal of Just and Carpenter

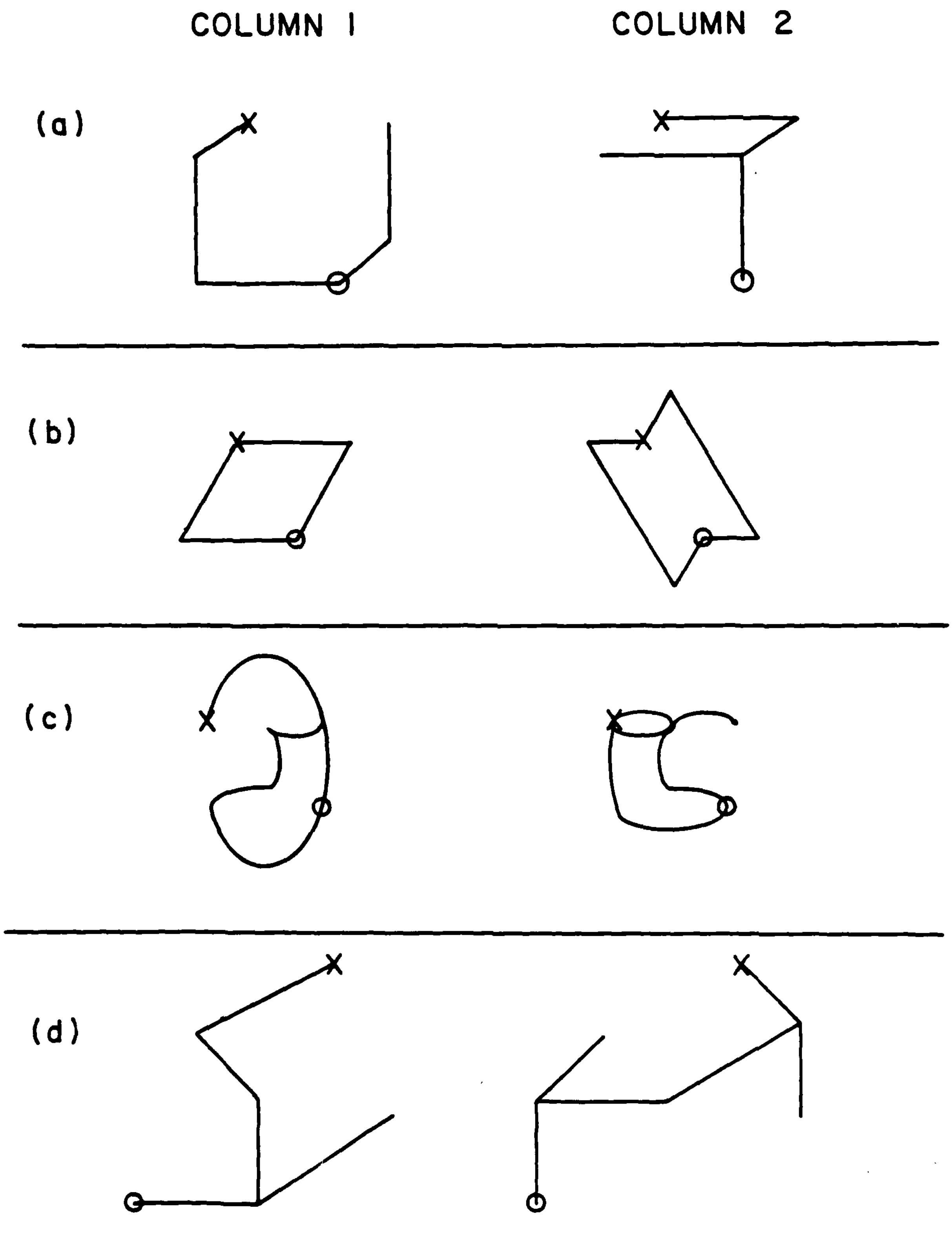


Fig. 8

(1976) although it is not identical to that proposal.

A major issue with the Shepard and Metzler figures is whether they are rotated as single objects or whether they are rotated and moved in pieces. Just and Carpenter claim they are rotated and moved in pieces. There is nothing critical to the piecemeal analysis because, as we will see, the piecemeal analysis assumes rotation operations on the fragments identical to those that the wholist analysis might want to propose for the full objects. However, it makes for a more interesting production system model to assume a piecemeal analysis and so I will. It may well be the case that inexperienced subjects, like those used by Just and Carpenter, rotate these figures in fragments whereas experienced subjects, like those used by Shepard and Metzler, rotate whole figures. I, a relative novice at mental rotation, have introspective experiences quite close to the piecemeal analysis modelled here.

I will assume that an image of one of these figures is hierarchically organized. Figure 9 illustrates how the overall figure is hierarchically decomposed into subfigures. The figure is analyzed into two overlapping elbows (sub-figures) and each elbow is analyzed into two overlapping arms (sub-sub-figures). I will assume that, for purposes of rotation, the arms need not be broken into individual cubes.

Insert Figure 9 about here.

Just and Carpenter identify three substages in the matching of these figures. The first substage involves finding parts of the two figures that correspond. The second stage involves rotating the part of one figure into congruence with the end part of the other figure. What this substage really accomplishes is to begin creation of an image which is the rotation of one figure. When completed this image will be matched to the other figure. The third substage completes construction of this image by moving copies of the remaining pieces of the figure to the image and testing for congruence. Just & Carpenter suggest that this third stage can either involve rotation or not; my model will assume no rotation for this third stage. Just and Carpenter call these stages search, transformation, and confirmation. My analysis maintains these distinctions but breaks each stage down into more information-processing detail.

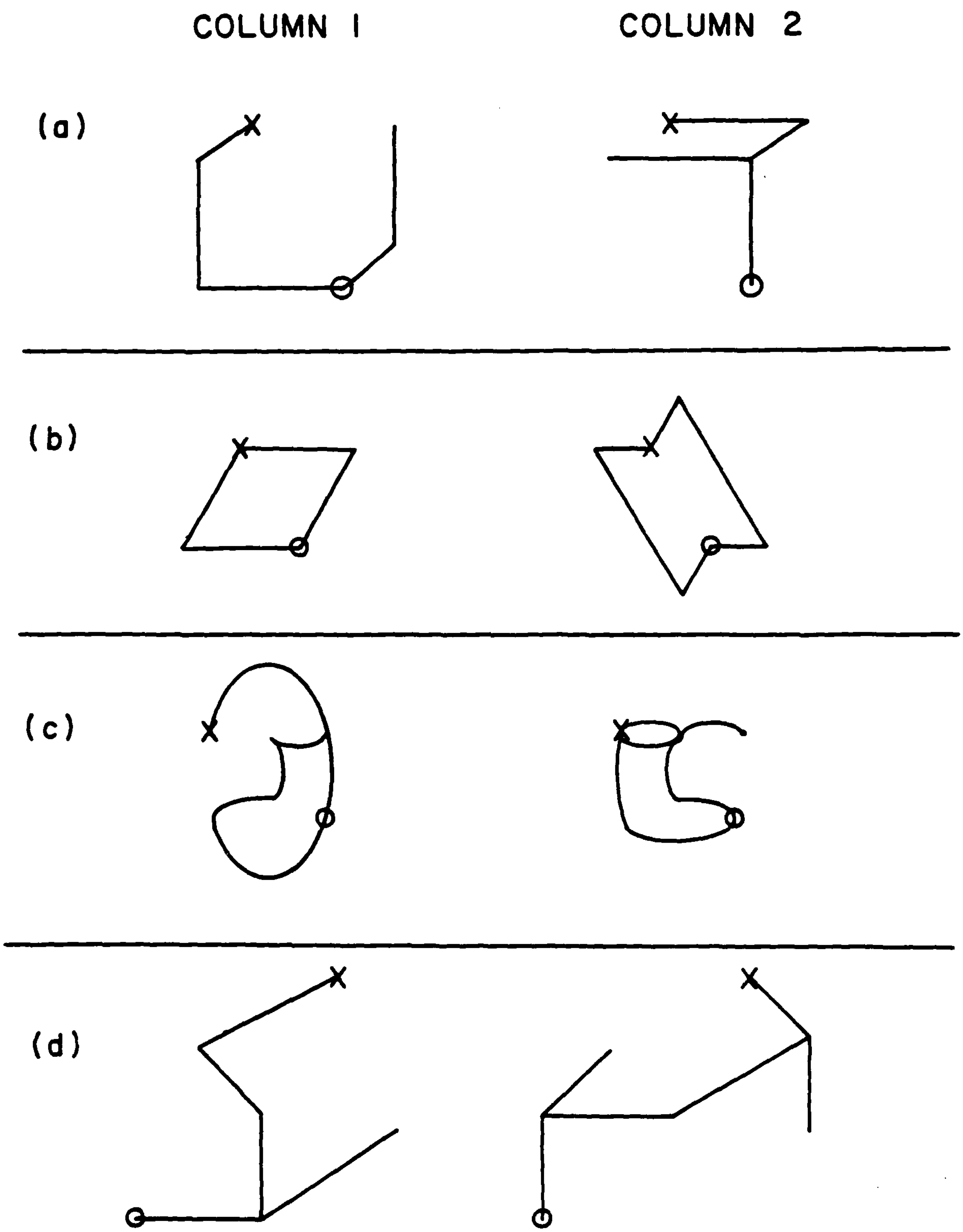


Fig. 8

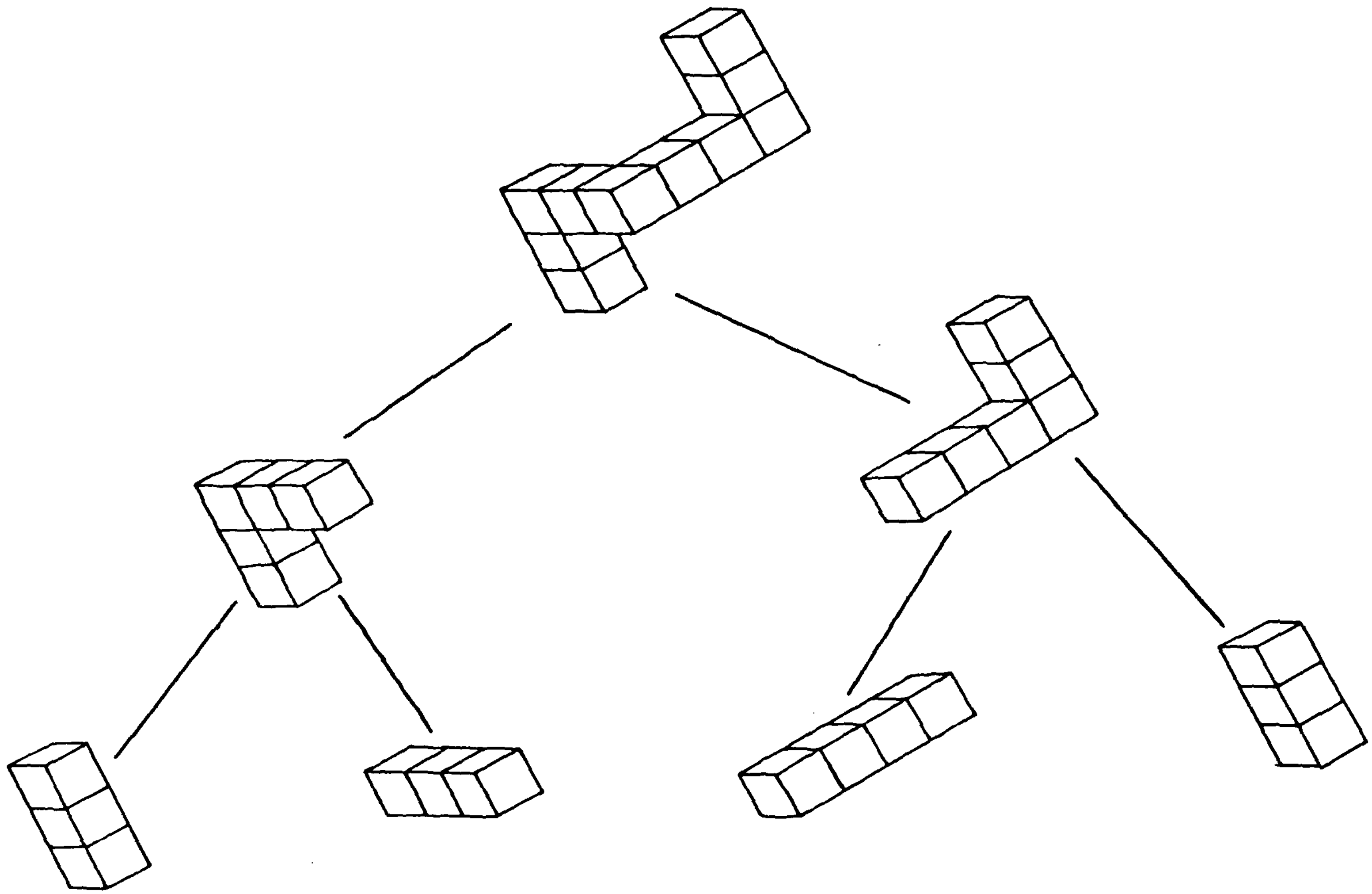


Fig 9

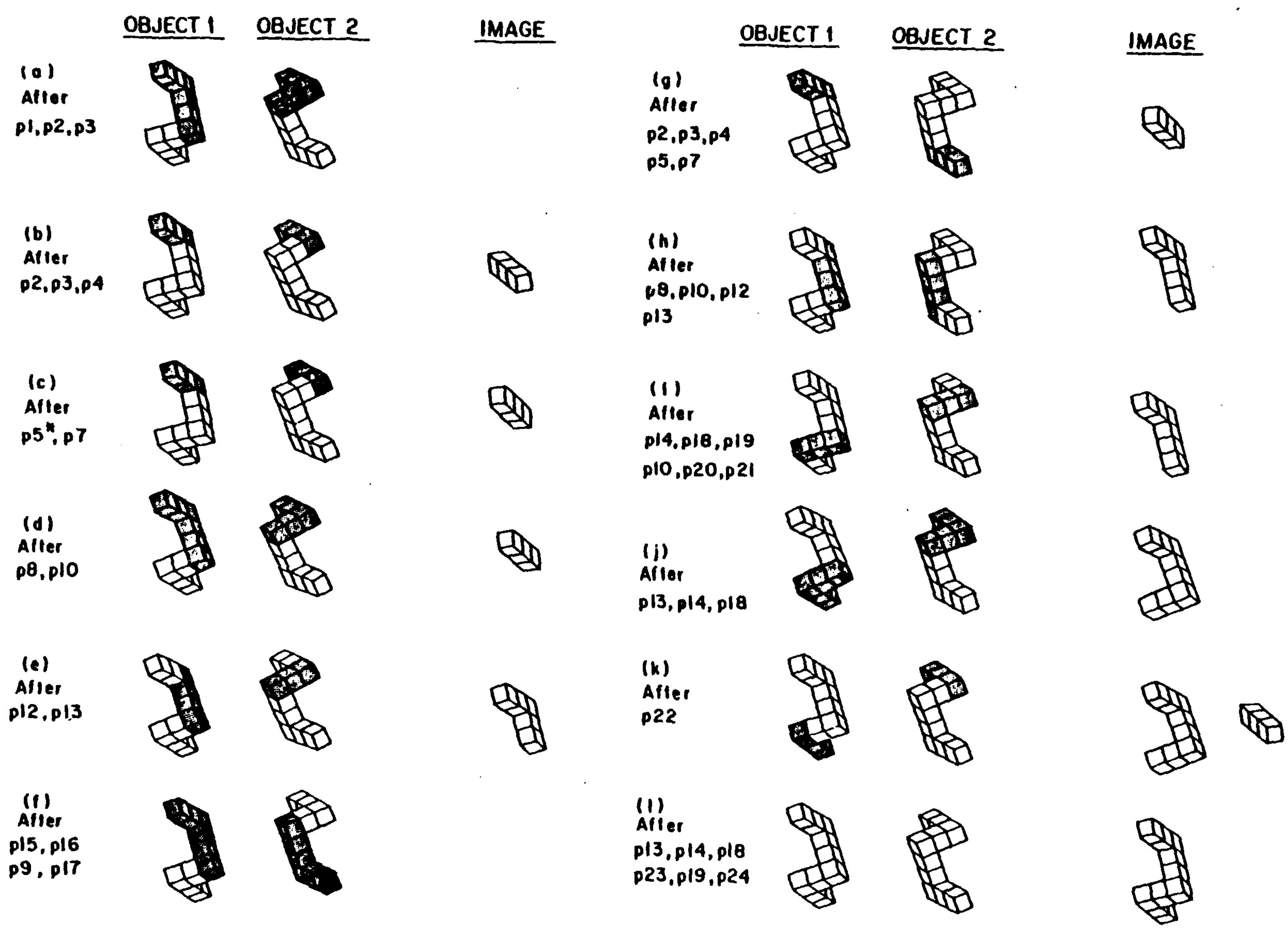

OBJECT 1
OBJECT 2
IMAGE
(a) After p1,p2,p3
(b) After p2,p3,p4
(c) After p5*, p7
(d) After p8,p10
(e) After p12,p13
(f) After p15,p16 p9, p17
OBJECT 1
OBJECT 2
IMAGE
(g) After p2,p3,p4 p5,p7
(h) After p8,p10,p12 p13
(i) After p14,p18,p19 p10,p20,p21
(j) After p13,p14,p18
(k) After p22
(l) After p13,p14,p18 p23,p19,p24

Fig. 10

Appendix II provides a detailed specification of the production system and its application to a problem. That production system will take two figures and try to create an image of one rotated into congruence with the other. Figure 10 is a summary illustration of the operation of that production system. It represents the two figures presented, the focus of attention on each figure (the shaded areas), and the contents of the mental image. The simulation starts out focusing on the two upper arms. In Figure 10b an image of the upper arm of object 2 is created and by a series of rotations it is transformed into congruence with the upper arm of object 1 (Figure 10c). When an attempt is made to attach the other arm in the upper elbow a mismatch is uncovered (Figure 10e). This leads to the abandoning of the attempt to make a correspondence between the upper parts of the two objects.

In Figure 10f an attempt is made to create a correspondence between the lower elbow of object 2 and the upper elbow of object 1. In Figure 10g an image is created of the lower arm of object 2 and it is rotated into congruence with the upper arm of object 1. Then in Figure 10h-10l, the various arm fragments are attached until a complete image is achieved. This production system predicts an effect of rotation angle in two places. First, greater angle increases the likelihood of false starts as illustrated in Figures 10a-10e. Second, a number of iterative rotations are required to align the initial segments (Figures 10c and 10g). The production system also predicts an effect of image complexity in terms of the number of separate pieces that need to be imaged (Figures 10b-10l).

This example illustrates that an imagery process is compatible with a production system architecture and that the distinct character of imagery derives from the distinct production processes it assumes. To the best of my knowledge, it is in fact an accurate model for the empirical phenomena. It clearly does predict the basic rotation result. It is consistent with the qualitative eye movement data of Just and Carpenter (1976). The theory makes an interesting set of predictions about the relationship between complexity and rate of rotation. As complexity will map onto number of subparts, there will be a complexity effect on judgment time. However, the actual rotation operation is only performed on a single part. Thus, there need not be an interaction between complexity and rate of rotation. On the other hand, greater complexity of the stimulus or greater angle of rotation can result in more false starts where the system starts out with one correspondence

and must try another. Thus, in situations where there is not a clear basis for anchoring the correspondences, there would be a multiplicative relationship between complexity and angle of rotation. This is a rather complicated prediction but it is at least consistent with the complicated and superficially contradictory empirical picture that exists about effects of complexity on rate of rotation (Cooper & Podgorny, 1976; Carpenter & Just, 1978; Pylyshyn, 1979; Shwartz, 1980). The eye movement data of Just and Carpenter particularly gives strong support to the idea that effects of angle of rotation are both due to rotation of a single part and due to false correspondences.

Functional Value of the Image Representation

It is worthwhile to review the properties that justify spatial images as a distinct representation type. They are the only data objects that encode interval information about a configuration of objects. Correspondingly, degree of match is a function of distance and configuration. Information about distance, direction and overlap are emergent properties. Images can be constructed by a rotation operation which has no analog in any other domain. Kosslyn (ref) has suggested a number of other such properties to distinguish images. Such processes have enormous adaptive value in dealing with spatial information. The emergent properties make readily available the kinds of information needed to navigate in one's environment and to process physical objects. The image rotation is clearly important because we live in an environment where orientation is not always constant. It is worth noting here again that many transformations such as shearing and four-dimensional rotation are not naturally calculated -- and presumably, one seldom comes upon new spatial configurations in the real world that are related to known configurations by such transformations.

It is also worth noting that, while there are some relatively powerful computational processes available with images, there are severe restrictions on the kinds of pattern matching that may successfully be performed on an image. Pattern matching with images is severely upset by changes in orientation or relative configuration (although not by changes in absolute size). Indeed, the work on mental rotation is predicated on just this fact. Just as matching of strings is strongly governed by order and first elements, so matching of images is strongly governed by relative position. The pattern-matcher thus structures itself differently to deal with different representations.

Abstract Propositional Representation

Encoding

Abstract propositional representations are in sharp contrast to temporal strings and spatial strings in the way they encode the information. First, they are abstract in that the code is independent of the order of the information in the environment. For instance, the propositional representation (hit John Bill) does not encode the difference between John hit Bill and Bill was hit by John. Encoding a scene of John hitting Bill the propositional representation does not code who is left and who is right. Second, it is abstract because it identifies certain elements as critical and ignores all else. Thus, the encoding of the scene may ignore all physical details about such things as John's or Bill's clothing.

One of the principle lines of empirical evidence for propositional representations comes from the various sentence memory studies that show semantic variables and not the word structure of the original sentence are predictive of memory performance. This research includes the long tradition of experiments showing that memory for gist is better than memory for wording (e.g., Begg, 1971; Bransford & Frank, 1971; Sachs, 1967; Wanner, 1968) and the experiments that show the best prompts for recall of a particular word in a sentence are other words which are semantically close (Anderson & Bower, 1973; Lesgold, 1972). Similar demonstrations have been offered with respect to picture memory (Baggett, 1975; Mandler & Ritchey, 1977) -- that is, it is the underlying semantic relations that are predictive of memory. In reaction against this research, there have been experiments which have demonstrated good memory for wording of sentences (Graesser & Mandler, 1975) or good memory for visual detail that is not semantically important (Kolers, 1978). However, these observations are not troublesome for the multi-representational position being advanced here although they can be embarrassing for the pure propositional position that has been advanced. What is important for current purposes is that there are highly reproducible circumstances where memory is good for the meaning of a stimulus event and not for the physical details of that event. To account for these situations it is necessary to propose a representation that extracts the significant semantic relationships from these stimuli. To account for situations that show good memory for detail one can use the temporal string or image representation.

Another distinct feature of abstract propositions is that there are strong constraints among the elements in a proposition. Thus, *hit* takes two arguments, *give* three, *know* must have one of its arguments be an embedded proposition. There is nothing like this with strings or images. One element of a string or image does not constrain what the other elements might be. Images and strings encode directly what is out in the world and basically any combination is logically possible. On the other hand propositions represent *relational categorizations* of experience and the mind has only learned to see certain patterns.

As with the other representations, the true significance of the abstract propositional representation becomes apparent when we specify how it is treated within the production system framework. Unlike the encoding processes for temporal strings or spatial images, the structure of an abstract proposition is not a direct reflection of environmental structure. Rather its encoding reflects an abstraction of an event and the encoding process itself is something that must be learned. This is clear with respect to language where each child must learn the processes of comprehension (sometimes innocuously called a "parser") for his particular native language. However, similar extraction processes must be at work in learning to interpret non-linguistic experiences and identify the meaningful invariances (innocuously called perceptual learning and concept acquisition). Because the propositional encodings are not direct reflections of external structure but are determined by experience, the representations that have been proposed over the years have tended to have a somewhat ad-hoc character to them. Until we specify the abstraction processes that underlie the formation of the perceptual and linguistic parsers, there will be unwanted degrees of freedom in propositional representations and they will remain as much a matter of intuition as of principle.

Notation. The semantic network notation is very appropriate for representing propositional structures. Figure 11 shows one such representation. A central node represents the proposition or semantic unit and links emanating from the central node point to the various elements of the proposition. Labels on the links identify the semantic relationships. The labelled network notation is appropriate because the links in a net are order-free just as are elements of a proposition. The reader may recognize such a representation as basically the structure introduced by Rumelhart, Lindsay, and Norman (1972) in the early days of the LNR model. Many other more complex network notations exist (e.g. Anderson & Bower, 1973; Norman & Rumelhart,

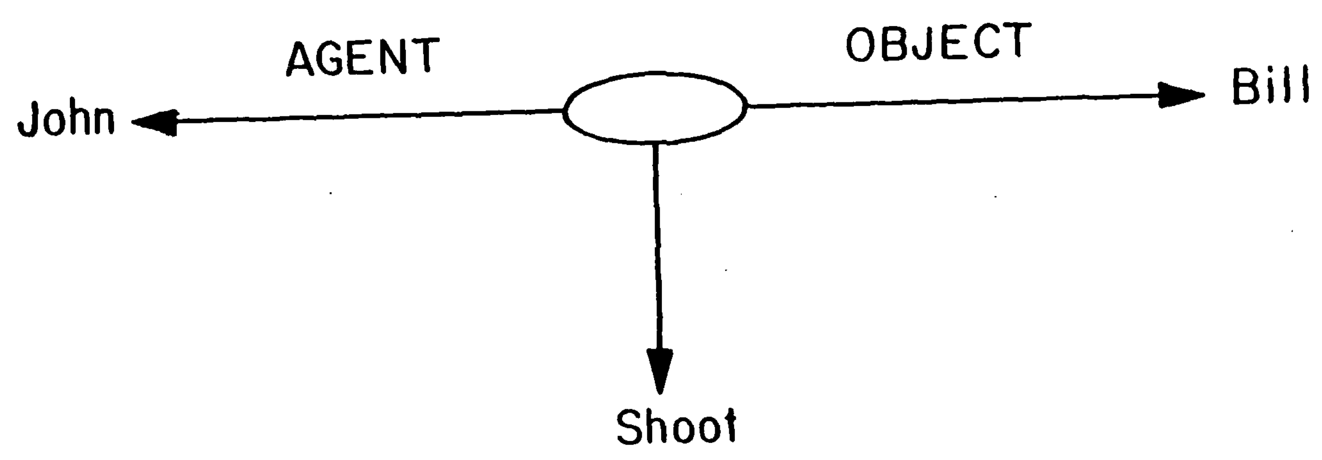
1975; Schank, 1972) and I will discuss some of the issues separating these representations. Kintsch (1974) introduced a linear notation for representing network structure which is more tractible for large sets of propositions than is a network representation like Figure 11, but the two notations are equivalent in information conveyed. In line with remarks made elsewhere in this paper I do not think that the differences between the various propositional notations are substantial. What is of substance are the various processes that operate on the representations.

Insert Figure 11 about here

All-or-none Storage and Retrieval

With respect to the storage and retrieval processes, I think it is reasonable to propose that propositions are encoded and retrieved in an all-or-none manner as I have proposed for strings and images. This is an issue about which there has been a mild debate (e.g., see Goetz, Anderson, & Shallert, 1981) and I have found myself on the other side of the issue (i.e. proposing partial memory for propositions). Recently, I (Anderson, 1980) have written an article recanting my position. The basic empirical research involves subjects' memory for sentential material where it seems reasonable to assume that certain phrases convey basic propositions. For instance, *The doctor shot the lawyer*, might be said to convey a basic proposition. It is sometimes observed that subjects cued for memory with part of a proposition, e.g. the doctor, may only recall back part of the remainder. This partial recall is a well-established fact and numerous theories have been developed to account for it (e.g. Anderson & Bower, 1973; Jones, 1978). However, a problem is that the degree of partial recall is much less than would be expected under some notions of chance. For instance, suppose we cue with subject and look at recall of the object conditionalizing on recall of the verb. The observation is that recall of the object is much higher conditional on recall of the verb than not. Depending on what experiment we cite, one observes 60% - 95% object recall conditional on verb and 3 - 15% object recall conditional on non-recall of verb.

I think this empirical evidence provides weak evidence at best on the issue of all-or-none memory for propositions and elsewhere (Anderson, 1976, 1980) I have tried to unpack the ambiguities. The degree of



Fis. 11

all-or-none recall is equivalent to that which lends support to all-or-none recall of phrases in strings. So, perhaps by a strange principal of equality we should accept the conclusion of all-or-none recall here. In contrast to the murkiness of the empirical picture, I think the evidence for an all-or-none system is quite strong from implementation considerations. Our experience in the production system framework has been that it is very non-adaptive to have partial propositions stored or retrieved. Such partial propositional information cannot be easily used in further processing and so its retrieval only clutters up working memory, or worse, misleads the information processing. It seems unlikely that an adaptive system would waste capacity on such useless, partial information. Thus, this is a case where our general framework can help guide a decision where the empirical evidence is ambiguous.

Perhaps facts of arithmetic are the easiest examples for purposes of illustrating the impact of partial encoding. Suppose we stored the proposition (5 = (PLUS 3 2)) as (= (PLUS 3 2)) where the sum has been omitted in a partial encoding. Clearly, such a fact is of no use in a system. Whether partial encoding leads to disaster rather just waste depends on one's system assumptions, but suppose one allowed propositions to encode facts like (6 = (PLUS 3 2 1). Then *imagine what a disaster the partial encoding* (6 = (PLUS 3 2)) could lead to! The crisp semantics associated with arithmetic propositions makes very clear the consequences of partial encoding. However, similar problems occur in an inferential system when we encoded (Reagan defeated Carter) as (defeated Carter) or (Give Mary Bill Spot last-year) as (Give Mary Bill Spot).

Pattern Matching: Emergent Properties

Subjects appear to have an ability to detect that elements are connected in a propositional representation before they can judge how. The ability to make connectedness judgments shows up in a wide variety of experimental paradigms, but it would be useful to describe an experiment from my laboratory which had as its goal to simply contrast judgments of connectness with judgments of form. Subjects studied simple subject-verb-object sentences like <u>The lawyer hated the doctor</u> and then saw test sentences that exactly matched (The lawyer hated the doctor), that had subject and object reversed (The doctor hated the lawyer), or that had one word change (e.g. The lawyer hated the sailor, The lawyer kicked the doctor). There were two types of judgments to be made. In the proposition-

Table 4
Mean Reaction Times in Seconds and Error Rates (in parentheses) for recognizing that a sentence has the same form as an original sentence versus that the sentence connects the same elements.

Probe Type	Judgment Task: Exact Match	Judgment Task: Connected
Exact Match	1.685 (.077)	1.573 (.056)
S-O Reversal	1.759 (.139)	1.634 (.074)
Overlap	1.725 (.083)	1.650 (.112)
Average	1.723 (.099)	1.619 (.081)

matching condition subjects were asked to recognize if a test sentence conveyed the same meaning as an original study sentence. Thus, they responded positively to the first type of test sentence and negatively to the other two types. In the connectness judgment task subjects were asked if all three words came from the same sentence. Thus, they responded positively to the first two types of test sentences and negatively to the third type. The results of the experiments are displayed in Table 4. Subjects responded uniformly more rapidly in the connectedness condition indicating that they do have access to information about whether a set of concepts are connected more rapidly than they have access to how they are connected.

Reder & Anderson (1980) and Reder & Ross (1981) also present evidence that subjects are able to make judgments of thematic relatedness more rapidly than exact connections. In that experiment subjects learned a set of thematically-related facts about a person -- for instance, a set of circus facts about John. Subjects could judge that a fact related to what they have studied faster than they could judge whether it was studied. So, for instance, subjects could judge *John watched the acrobats* was consistent before they could decide it was studied. I (Anderson, 1983) have proposed that subjects make this relatedness judgment by detecting a propositional connection between the probe fact and the facts stored in memory.

In many circumstances this rapid detection of connectivity can interfere with the rejection of a foil. Collins & Quillian (1972) report that subjects find it difficult to reject *Madrid is in Mexico* because of the spurious connection. Glucksberg & McCloskey (1981) have found subjects find it easier to decide that they don't know a fact like *John has a rifle* if they have learned nothing connecting *John* and *rifle* than if they have explicitly learned the fact that *It is not known whether John has a rifle*. Anderson & Ross (1980) showed subjects were slower to reject *A cat is a snake* if they had learned some irrelevant connecting fact like *The cat attacked the snake*. King and Anderson (1976) report a similar effect in an experiment in which subjects are to retrieve experimentally-learned facts.

Pattern Matching: Degree of Match

Because of their non-analog character, there is missing a notion of closeness in the matching of propositions that is present in the matching of strings and images. The degree of partial match of a propositional pattern is simply a function of the number of elements in the pattern successfully matched. Also because the elements

composing a proposition have a set character we do not see the order dependence in proposition matching as we saw, for instance, in string matching. Subjects are much better able to recognize a substring of elements if they are the beginning part of the original string. This is not so with propositional material. For instance, in my research on sentence recognition (Anderson, 1976; Ch. 8) I found that any subset of elements from a proposition is recognized as well as any other subset and order of elements does not matter. Dosher (1976) reports a similar conclusion.

There is a natural tendency to think of propositions and word strings as really being the same - a single, verbal representation (e.g. Begg & Paivio, 1969). However, propositions strongly contrast with strings in that they do not have the order dependency that we find for strings. To illustrate this, I performed the sentence analog to the experiment reported in Table 2 on letter strings. We had subjects commit to memory location-subject-verb-object strings like <u>In the subway the doctor helped the writer</u>. Subjects were encouraged to treat these as meaningful propositions by instructions which required them to elaborate a short story about each. As in the letter string experiment, subjects also had to associate a digit in the range 0 - 9 to each sentence. They were drilled in recalling the sentences to the digits until they had given four perfect recalls of each sentence. Then they were switched to a task where they saw some subset of the four words in the sentence and they had to recall the corresponding digit. As in the letter string experiment each word occurred in two sentences but subjects could uniquely identify the digit on the basis of any pair of words.

Insert Table 5 about here.

The results of this experiment are displayed in Table 5 which is to be compared with Table 3 for the earlier experiment. The data in this experiment are in sharp contrast with that of the string recognition experiment. Subjects are slowest when the probe begins with the location, the first content word studied in the sentence. Except for this, there is no apparent effect of elements and little difference depending on whether the sentence begins with subject, verb, or object. Dosher (1976) and Goetz, Anderson, Schallert (1981) have also observed that the location seems not as integrated with the sentence as the other terms. This suggests that subject, verb, and object should be considered an embedded cognitive unit. A higher propositional unit

Table 5
Mean Reaction Times in Seconds and Error Rates (in parenthesis) for the Proposition Naming Experiment

Location of First Letter	Location of Second Letter	2-tuples	3-tuples	4-tuples	Mean
		2.69	3.10	3.11	2.97
1	2	(.05)	(.05)	(.05)	(.05)
		2.73	2.80	2.66	2.73
1	3	(.06)	(.06)	(.04)	(.05)
		2.84	2.61	2.48	2.64
1	4	(.07)	(.05)	(.04)	(.05)
		2.66	2.32	2.21	2.36
2	1	(.06)	(.04)	(.05)	(.05)
		2.32	2.17	2.16	2.22
2	3	(.07)	(.03)	(.04)	(.05)
		2.37	2.25	2.23	2.28
2	4	(.07)	(.04)	(.03)	(.05)
		2.28	2.22	2.14	2.21
3	1	(.08)	(.04)	(.03)	(.05)
		2.20	2.23	2.12	2.18
3	2	(.04)	(.04)	(.04)	(.04)
		2.16	2.01	2.08	2.08
3	4	(.04)	(.04)	(.03)	(.04)
		2.38	2.19	2.05	2.21
4	1	(.07)	(.04)	(.04)	(.05)
		2.40	2.11	2.08	2.20
4	2	(.07)	(.05)	(.03)	(.05)
		2.06	2.01	2.11	2.06
4	3	(.03)	(.03)	(.03)	(.03)
Mean		2.42	2.34	2.29	2.35
		(.06)	(.04)	(.04)	(.05)

connects the location and the embedded unit with a specification that the event described by the embedded proposition occurred in the location. Curiously, this is like the HAM representation proposed by Anderson & Bower (1973).

Construction of Propositions

As with images and strings, propositions can be created by combining elements which may be primitive or may themselves be propositions. However, the relational structure of a proposition imposes a unique property on proposition construction. The relation takes a fixed number of slots, no more or no less. This means that when a relation is constructed but not all the arguments specified, the missing arguments will be filled in by default. Thus, if we hear "Fred was stabbed", we cannot help but fill in a dummy agent. The various proposals for propositional systems differ in how rich a system they propose for default slots and inference procedures to fill these slots. So, one feature that tends to accompany proposals for "semantic decomposition" (e.g., Schank, 1972; Norman & Rumelhart, 1975) is a rich system for inferring the occupants of various slots. However, all propositional systems by their very nature require some default system for filling in missing slots. The notation of a missing slot is not a meaningful one for images or strings.

Function of a Propositional Code

Clearly, the distinctive properties of propositions derive from their abstract set-like structure and their relational structure. People learn from experience which aspects or higher-order properties of an event prove to be significant and so they develop a code to represent these. There are a number of advantages to such a code. First, it is more direct and efficient. Rather than representing all the pieces of information that enable the inference that A has thrown a ball (e.g. A raised his hand over his head, A's hand held round object, etc.) or the exact words of the sentence that was parsed into this meaning, the significant relationship is represented directly. The propositional representation does yield an economy of storage in long-term memory but it has other advantages probably more significant. For instance, the representation will occupy less space in working memory and will not burden the pattern matcher with needless detail. Thus, it will often be easier to manipulate (i.e. think about) these abstracted structures.

General Conclusion

Refer back to Table 2 for a summary of the process features that distinguish the three types of representation: They encode different types of information, have different pattern-matching principles, and have different principles of construction. The mere fact that different knowledge is processed differently would not be so interesting as what is represented in Table 2. The claim there, which was argued at length in the paper, is that large sets of knowledge have exactly the same differences. For instance, every image differs from every proposition in just these properties. This is the empirically significant claim in this paper.

One might question whether these processes are really distinct. To consider a wild but instructive example, suppose someone proposed the following "propositional" model to account for distance effects in judging relative position in a linear ordering. Each object is given a propositional description that uniquely identifies its position. So, the string ABCDEFGH might be encoded as follows: A's position is 0 followed by 0 followed by 0. B's position is 0 followed by 0 followed by 1, etc. where we basically encode each position in binary. To judge the order of two items subjects would have to retrieve their binary encodings and then have to scan their encodings left to right until a first mismatching digit was found. Then a judgment could be made. The further the items are apart the fewer propositions that need to be scanned <u>on the average</u> to find a mismatch. There are numerous challenges that one could make to this proposal but I would like to focus on one for current purposes. The time to make linear-order judgments (often less than a second) are clearly less than the times to chain through three propositions in memory (seconds). Thus, there is no way to get the temporal parameters right for the propositional model. This illustrates an important constraint that blocks many creative attempts to reduce one process to another, supposedly more basic process. The time measures for the basic processes must add up to equal the reduced process.

Storage and Retrieval

An interesting observation about Table 2 is that there appear to be no differences among the three data types in terms of how they are stored in long-term memory or how they are retrieved. This means that memory experiments such as Anderson & Paulson (1978) and others that attempted to find different types were doomed to failure. For all three types of representation there is a basic unit or storage -- be it the phrase,

image, or proposition. In each case the size of such a unit is severely limited by the number of elements that can be kept active in working memory. A unit can be thought of as a *form* with a number of *slots*. In the case of strings, the form is the linear ordering and the slots are the elements ordered. In the case of an image, the form is the spatial configuration and the slots are the objects configured. In the case of propositions, the form is the relation and the slots are the arguments of that relationship. In all cases there is a restriction on the number of slots that a form can have.

The basic claim is that the form plus its slots, while being held in working memory, can be fixated into long-term memory. If it is so fixated all elements of the form will be deposited into long-term memory. Hence the process of storage is all-or-none. Similarly, the process of retrieval is all-or-none: If a form is retrieved back into working memory all of its elements are.

I have suggested (Anderson, 1980) that the term *cognitive unit* be used for structures that have these storage and retrieval properties. Thus, all these representational types, strings, images, and propositions, are cognitive units. I have already reviewed some of the evidence for the all-or-none character of memory for these various representational types. However, it is also the case that in no experiment does one ever observe perfect all-or-none recall. This leaves the issue of how to explain residual partial recall. I think such partial recall can be explained by a combination of assumptions about hierarchical encoding and multiple codes.

Because of limits on how much can be encoded into a single unit, large of knowledge structures must be encoded hierarchically in which smaller cognitive units are embedded within larger cognitive units. It has been suggested (Broadbent, 1975) that the limitations on unit size are related to the limitations on the capacity of working memory to access related information in working memory. Basically, for a unit to be fixated into long-term memory all of the elements must be in working memory and the ~~success~~ system must be able to uniquely point to each. Broadbent notes that the number of elements in a chunk correspond to the number of values one can keep separate on physical dimensions. He suggests that problems with larger chunks might be "discrimination" problems in identifying the locations of the individual elements in working memory.

One can retrieve an hierarchical structure by a top-down process which he starts with the top structure,

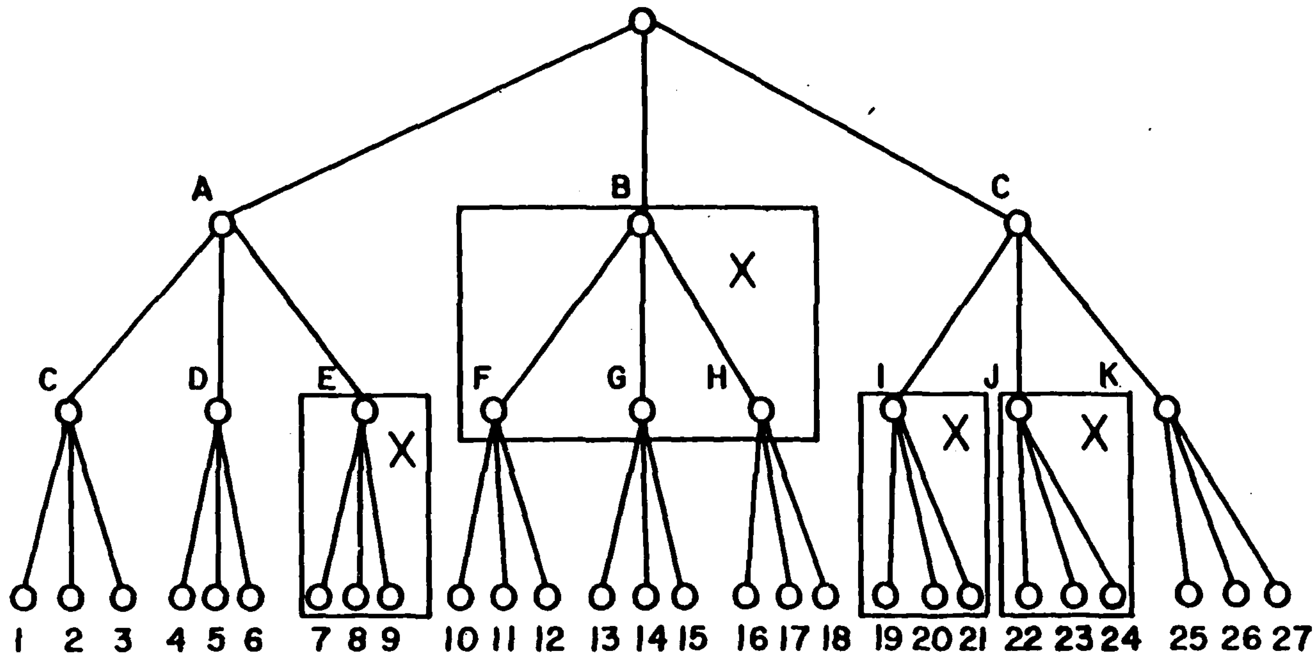
unpacks it into its elements, and unpacks these, and so on until the terminating elements are reached. Similarly, it is possible to do retrieval in a bottom-up manner -- start with a terminating element, retrieve its embedding structure, retrieve the structures that embeds it, and so on until the top structure is retrieved.[3] These steps of retrieval can fail. They can fail either because the unit to be retrieved was not encoded or because it cannot be retrieved.

Figure 12 presents a hypothetical hierarchical structure in which certain X'd units are marked as unavailable for recall. There are 27 terminal elements. Using a top-down search it would be possible to retrieve A, B, and C from the top structure, C, D, and E from A; 1, 2, and 3 from C; 4, 5, and 6 from D; the structure from E is not available; nor is the structure from B; I, J, and K can be retrieved from C; the structure from I and J are not available, but 25, 26, 27 are available from K. Thus, although each individual act of retrieval was all-or-none only 9 terminal elements were retrieved from the 27 element terminal array. Also note that, cued with 10, the subject would be able to retrieve the fragment F and hence the element 11 and 12 but nothing else of the hierarchy. Such hierarchical retrieval would produce the phrase patterns documented for linear strings (Johnson, 1970); propositional structures (Anderson & Bower, 1973); and story structures (e.g. Owens, Bower, & Black, 1979; Rumelhart, 1978). To my knowledge no one else has explored the issue with respect to picture memory; but it would be surprising if such hierarchical recall structures were not also found there.

Insert Figure 12 about here

If one could segment a to-be-recalled structure into its hierarchical units, then one should see all-or-none recall for the separate units. The empirical phenomena is never as strong as all-or-none recall under such attempts at analysis. One reason for this is subjects are not entirely consistent in the hierarchical encoding schemes that they adopt. Their hierarchical structure might differ slightly from the one assumed by the experimenter.

A more important reason for deviation from hierarchical all-or-none recall is that the subject may produce



A
B
C
C
D
E
F
G
H
I
J
K
X
X
X
X
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27

Fig. 12

elaborations which deviate from the specified hierarchy. For example, consider subject memory for The rich doctor greeted the sick banker. A hierarchical analysis would assign rich and doctor together. However, a subject might elaborate on the connection between rich and banker or between doctor and sick. Then, in recall, the subject may recall sick and doctor but not rich and banker, violating the expected all-or-none pattern. I have discussed the complications produced by subject elaborations in Anderson (1976). So all we can expect to see is a tendency in the direction of all-or-none recall. This also means that such empirical phenomena are only weak support for assumptions about all-or-none memory. I think the stronger evidence comes from our experience with the non-adaptiveness of partial recall in a production system (Anderson, 1980). As noted before, it is at best useless to retrieve a partial structure and at worst disastrous.

Mixed Hierarchies and Tangled Hierarchies

To this point the discussion has largely assumed hierarchies consisting of units of the same representational type. However, there is no reason not to suppose that representational types might be mixed and there is some clear advantage to having this flexibility. If one wanted to represent "John chanted 'one, two, three'", it is clearly more economical to represent the object of John's chanting as a string. That is, the string would appear as an element of a proposition. Again, if one wanted to represent the sequence of events at a ball game, one might want to have a linear ordering of a sequence of propositions describing the significant events. Strings and images would be mixed if one wanted to represent a spatial array of nonsense syllables, or a sequence of distinct images. Again we would want a mixture of images and propositions, if one wanted to encode comments about pictures or encode the position of various semantically-significant objects without encoding the visual details of the object (e.g. Figure 4c).

Our discussion of these hierarchies has assumed that a particular element or subtree appeared in only one hierarchy, but much of the expressive power of the system derives from the fact that hierarchies share subexpressions creating *tangled hierarchies.* So, for instance, the same image of a person can appear in multiple propositions encoding various facts about the person. Hierarchies can overlap in their terminal nodes also, as in the case of two propositions out of the same concept.

One can have very intertangled hierarchies such as Figure 13 which is inspired by the script from p.43 & 44

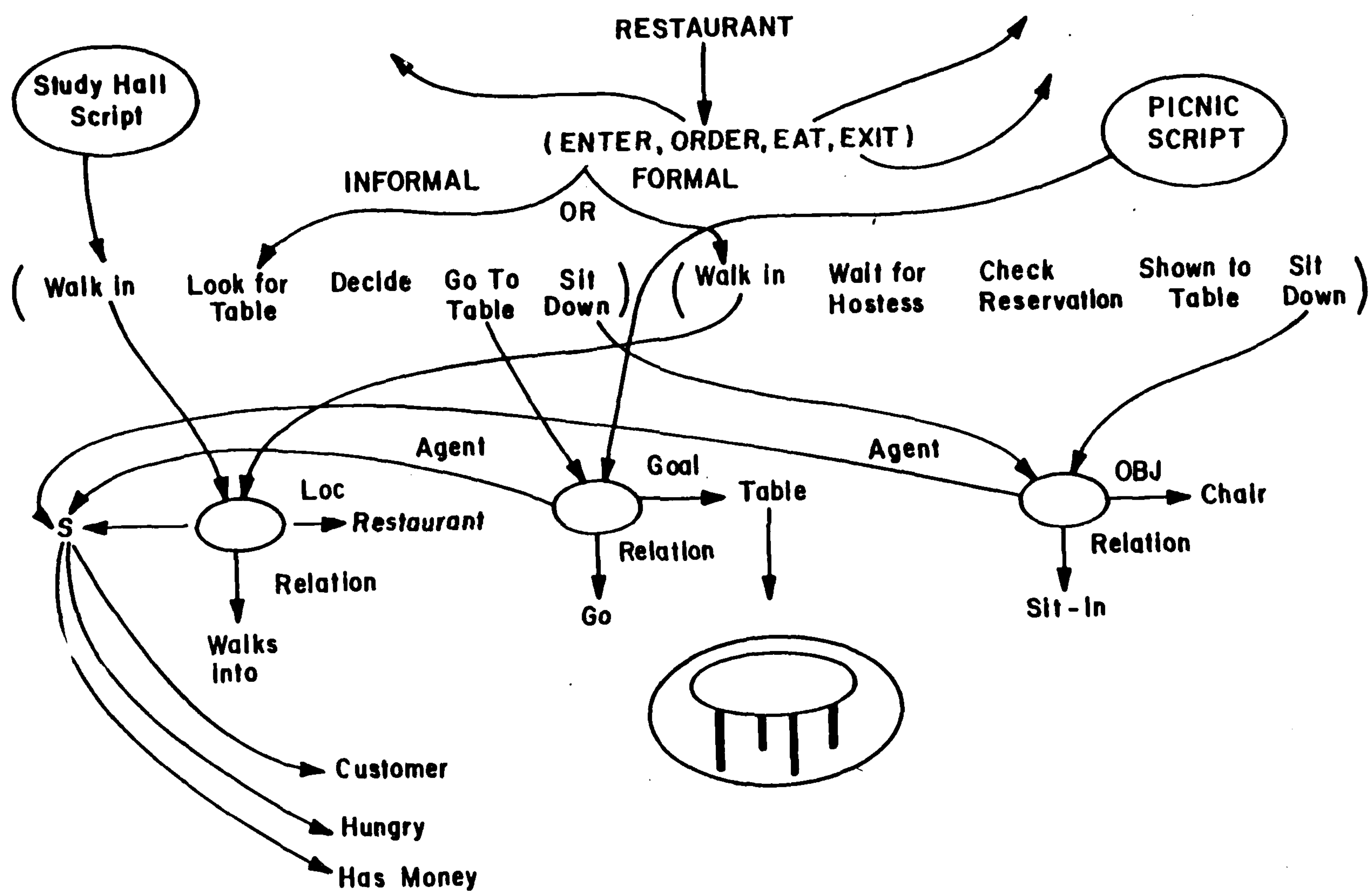
of Schank and Abelson (1977). Note that the central structure is a *hierarchical string of events* but various propositions and images overlay this string. In general, I think what Schank and Abelson refer to as a script will correspond to central temporal string overlaid with embellishing information. Schank's more recent proposal of MOPs (Schank, 1980) come closer to the generality of this tangled hierarchy concept.

Insert Figure 13 about here

Summing Up

The basic argument put forth in this paper is that, if we make different production system processes the criteria for discriminating among representations, then a rich array of empirical data point to the existence of *multiple types of data representation*. This multiple-types conclusion also seems justified from the point of view of the evolution of an adaptive system. The majority of this paper was devoted to documenting evidence for three types of representation and articulating properties of these three representational types. Finally, the paper concluded that, with respect to storage and retrieval from long-term memory, these three representations may share strong process commonalities. The critical concept for purposes of long-term memory is the notion of the cognitive unit of representation in which information is stored and retrieved. We noted that these units could enter into hierarchies of a variety in which different representational types were mixed. The fact that the three types differ in terms of how the procedural system treats them but are alike in their treatment by the declarative system, is one further piece of evidence for the utility of the procedural-declarative distinction that underlies ACT.

I have argued for three representational types on the bases of different processes defined on each. However, at some level, these processes are not distinct. Probably, they can be decomposed into the same principles of neural processing. If not, they can surely be decomposed into instantiations of the same set of physical laws. However, these are clearly the wrong levels of analysis. Our level of analysis is dictated by the adoption of the production system framework. Within that framework, the basic processes are those that are concerned with interfacing declarative and production memory (see Fig. 1) with working memory. Evidence for this framework is the fact that the processes are well-behaved in such a framework and lead to a systematic



RESTAURANT
(ENTER, ORDER, EAT, EXIT)
Study Hall Script
PICNIC SCRIPT
INFORMAL
OR
FORMAL
(Walk In
Look for Table
Decide
Go To Table
Sit Down)
(Walk In
Wait for Hostess
Check Reservation
Shown to Table
Sit Down)
Agent
Agent
Loc
Restaurant
Relation
Walks Into
Goal
Table
Relation
Go
OBJ
Chair
Relation
Sit-In
S
Customer
Hungry
Has Money

Fig. 13

identification of representational types.

The evidence for a general framework like the ACT production system architecture, will depend on whether it is possible to develop successful theories in that framework. (Note success or failure of a particular theory is not critical.) The architectural notions are at such a level of abstraction that more direct empirical evidence is impossible to achieve. So, we have a relationship of mutual dependency between this representational theory and the production system architecture. The production system framework is to be evaluated in terms of the success of the theories such as this tri-code proposal and this tricode proposal depends on the framework for its precise interpretation.

Footnotes

This research is supported by ONR contract N00014-81-C-0335 and by grant BNS78-17463 from the National Science Foundation. I would like to thank Susan Fiske, Keith Holyoak, Stephen Kosslyn, Zenon Pylyshyn, and Lynne Reder for their helpful comments on earlier versions of this manuscript and the members of the ACT research group (Gary Bradshaw, Bill Jones, Matt Lewis, Rolf Pfeifer, Peter Pirolli, and Jeff Shrager) for their discussions of the ideas in this paper. Correspondence concerning this manuscript should be sent to John R. Anderson, Department of Psychology, Carnegie-Mellon University, Pittsburgh, Pa. 15213

[1]In most production systems, matching working memory is not a sufficient, only a necessary condition for the production to execute. In addition there are *conflict resolution principles* which select some or perhaps only one of the concurrently matching productions for execution.

[2]I use the term *tri-code theory* rather than *tri-representational theory* to make it clear that I am concerned with a very basic level of representation. One could use the term representation to refer to issues such as whether, in representing the concept of apple, one should include facts such as they are used for making fruit pie. While perfectly legitimate issues to be concerned with, this is not my concern here. Rather I am concerned with the *code* and not the content of the representation. The term tri-code also, of course, derives as an extension of Paivio's (1971) use of dual-code.

[3]As will be discussed with respect to tangled hierarchies a unit may be an element of more than one larger structure. In this case there is an ambiguity in going up as to which larger structure to retrieve. The subject must use features such as other elements of the structure or contextual tags to select the correct structure.

Appendix I

I will first review in slightly more sophisticated *form* the argument given in Anderson (1976, 1978) that it is not possible to empirically distinguish between representational notations. Then I go on to show that within this framework there is a notion of distinct representational types at a level more abstract than that of notation. The formal argument concerns when two cognitive systems, CS and CS* with different representational notations would be equivalent. Figure 14 illustrates schematically the processing in these two systems. In part (a) we have a representation of system CS. It has an encoding process, E, that maps various stimulus situations (denoted by the S_i) into internal structures (denoted by some of the I_i). These internal representation I_i can be transformed internally into other representations I_j by a process T. Finally some of the internal representations are mapped into responses (R_i) by the response process (R). The system CS* has the corresponding components.

Insert Figure 14 about here.

A theory of representational notation resides in the structure of the description of the internal I_i. Thus, we might describe the I_i by relational propositions or by n-dimensional matrices. The choice of such a notation, by itself, results in no behavior. To have a system capable of observable behavior we must also specify an encoding process, E; process of internal transformation, T; and a response process, R. The question concerns under what circumstances can a different representational theory, CS*, with different descriptions of internal I_i^*, result in the same behavior as CS. Part (b) of Figure 1 illustrates such a mimicking system. It is possible to construct E*, T*, and R* for this theory of representation that mimic all the moves of E, T, and R.

Before exploring the issue of when such mimicry is possible it is necessary to become more precise in our terminology. The framework in Figure 14 glosses over some complexities that will prove important in the current discussion. First, the internal representation I_i in Figure 14 should be thought of as composed of sets of units. For instance, one of the encoding operations might be to map a sentence into a set of propositions representing its meaning. Also, the same set of units will not participate in all operations. Thus, a subset of the propositions derived from a sentence may join with other propositions to lead to an inference (an internal

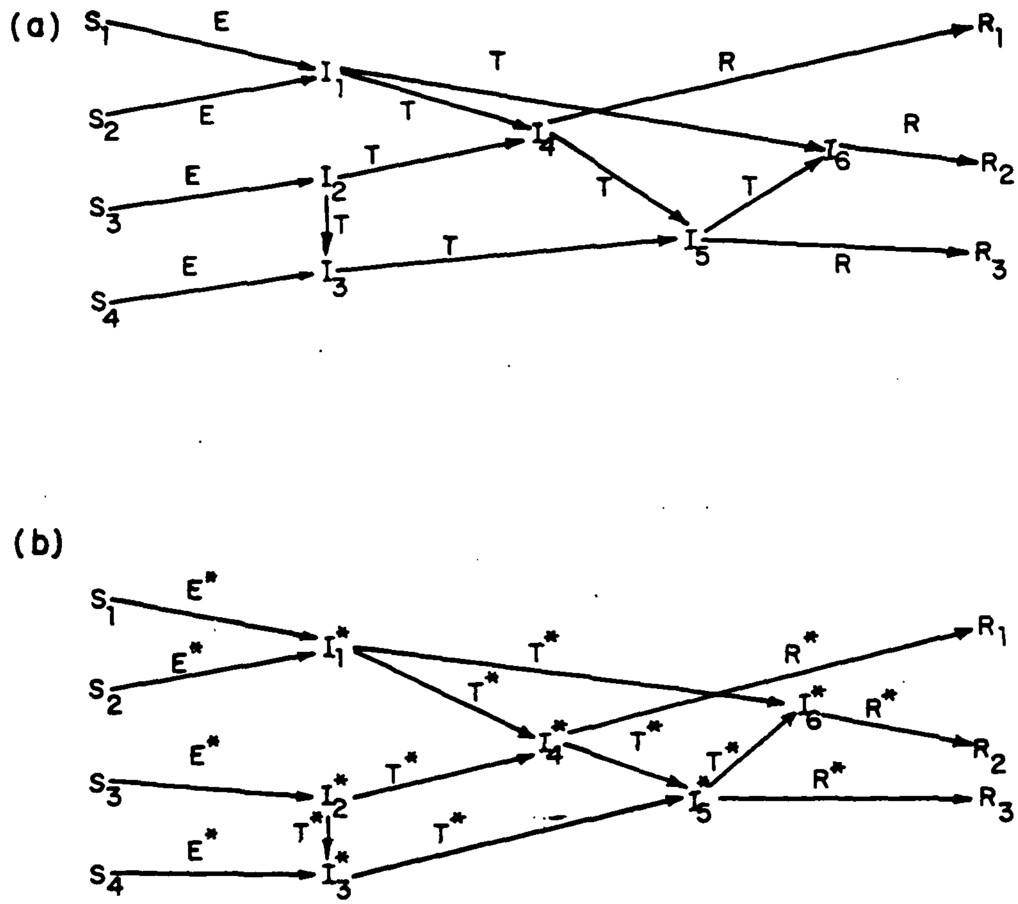

(a)
S1
S2
S3
S4
E
E
E
E
I1
I2
I3
I4
I5
I6
T
T
T
T
T
T
T
R
R
R
R1
R2
R3
(b)
E*
E*
E*
E*
I1*
I2*
I3*
I4*
I5*
I6*
T*
T*
T*
T*
T*
T*
T*
R*
R*
R*

Fig. 14

transformation). This is not easily represented in a schematic structure like Figure 14. An important complication concerns the E, T, and the R operations. There is probably not a single type of internal encoding, transformation or response generation. Different E might map the same stimulus onto different I_i. Different types of T or R may map the same I_i into different objects.

Definition of Equivalent Systems. Thus, for current purposes we will consider our system to be a four-triple $S = \langle \mathcal{E}, \mathcal{I}, \mathcal{T}, \mathcal{R} \rangle$ where $\mathcal{E}$ is the set of encoding operations; $\mathcal{I}$ is the set of all cognitive i_x where each I_i in Figure 14 is a set of i_x, where $\mathcal{T}$ is the set of internal transformations, T_i, operating on sets of cognitive units; and where $\mathcal{R}$ is the set of response operations R_j operating on unit sets. We are now ready to specify when one system CS will be isomorphic to another system CS* in its behavior. This will be defined with respect to a set of three equivalence relations on the components $\mathcal{E}$, $\mathcal{I}$, $\mathcal{T}$, and $\mathcal{R}$. There is an equivalence relation $\underset{I}{\approx}$ between the units of $\mathcal{I}$ from CS and $\mathcal{I}^*$ from CS*. We denote the equivalence between two units i_x and i_x^* as $i_x \underset{I}{\approx} i_x^*$. We say two sets I and I* are equivalent if for every $i_x \in I$ there is an $i_x^* \in I^*$ such that $i_x \underset{I}{\approx} i_x^*$ and vice versa. This, we denote as $I \underset{I}{\approx} I^*$. There is an equivalence relation $\underset{E}{\approx}$ between $\mathcal{E}$ and $\mathcal{E}^*$ such that for each $E \in \mathcal{E}$ there is an $E_i^* \in \mathcal{E}^*$ where $E_i \underset{E}{\approx} E_i^*$ and vice versa. Similarly, there are defined equivalence relations $\underset{T}{\approx}$ and $\underset{R}{\approx}$.

Definition of Equivalence. There is an equivalence relation $\approx$ between two systems $CS = \langle \mathcal{E}, \mathcal{I}, \mathcal{T}, \mathcal{R} \rangle$ and $CS^* = \langle \mathcal{E}^*, \mathcal{I}^*, \mathcal{T}^*, \mathcal{R}^* \rangle$ if there are equivalence relations $\underset{E}{\approx}$, $\underset{I}{\approx}$, $\underset{T}{\approx}$, and $\underset{R}{\approx}$ such that

1. For all stimuli S, E_i, and E_i^*, if $E_i \underset{E}{\approx} E_i^*$ then $E_i(S) \underset{I}{\approx} E_i^*(S)$

2. For all I, I*, T, and T*, if $I \underset{I}{\approx} I^*$ and $T \underset{I}{\approx} T^*$, then $T(I) \underset{I}{\approx} T^*(I^*)$

3. For all I, I*, R, and R*, if $I \underset{I}{\approx} I^*$ and $R \underset{R}{\approx} R^*$, then $R(I) = R^*(I^*)$

This definition guarantees that the relations illustrated in Figure 14 will hold everywhere.

Sufficient Condition for Mimicry. If we take a theory of representation to be a theory of the description of cognitive units, then a theory of representation lies in the choice of $\mathcal{E}$ and $\mathcal{I}$. It is necessary to specify $\mathcal{E}$ as

well as $\mathcal{D}$ so we know what the units in $\mathcal{D}$ are describing. (It is the case that some of the units in $\mathcal{D}$ may not correspond to any external event and may only be derivable from internal transformations). In Anderson (1978) I showed under what circumstances two theories of representation -- $\mathcal{E}$ and $\mathcal{D}$ on one hand and $\mathcal{E}^*$ and $\mathcal{D}^*$ on the other -- were not behaviorally distinguishable. The result in Anderson was that, if there was an equivalence relation $\tilde{=}_I$ on the internal representation so that part (1) of the equivalence definition held, then one could always construct $\mathcal{T}^*$ and $\mathcal{R}^*$ so that parts (2) and (3) of the equivalence definition held.

If two theories of representation impose the same equivalence class on external stimuli, they can be made to mimic each other. The important observation in this result is that it does not at all matter how the i_x of a theory are described to what their behavior predictions are. All that matters is that they impose the same equivalence class on external stimuli -- i.e., that for all S, $E(S) \tilde{=}_I E^*(S)$. Thus, if one theory uses propositions as the sole internal description, another uses just pictures, and a third uses just sentences (word strings), they will not be distinguishable behaviorally if they impose the same equivalence classes on external stimuli. By same equivalence class I mean that, if one maps a set of external stimuli onto one representation I, all map just that set of stimuli into one representation. If they do, it will be possible to construct the equivalence relations $\tilde{=}_I$ on representations that guarantee overall equivalence in behavior. So, for example, if the propositional system maps 513 distinct situations onto a proposition boy (a) & girl (b) & hit (a,b), the image system would create the same image of a boy hitting a girl for all and just these 513 situations, and the sentence system would represent all and just these situations by "The boy hit the girl".

The upshot of all this is that issues of how to describe cognitive units are not issues with behavioral consequences unless one system of description makes discriminations the other does not. The issue remains as to whether there is anything to the claims that there are various representational types -- whether it makes sense to talk of propositions, images, and strings. The key to the definition of cognitive types lies in the definition of equivalence above. We can construct an abstract cognitive system $CS+ = \langle \mathcal{E}+, \mathcal{D}+, \mathcal{T}+, \mathcal{R}+ \rangle$ for any equivalence class of cognitive systems. The encoding operator $\mathcal{E}+$ for this abstract system will consist of operators that are formed from the equivalence classes of operators taken from the individual $\mathcal{E}$. Similarly, we will define $\mathcal{D}+$, $\mathcal{T}+$, $\mathcal{R}+$. So, suppose $CS = \langle \mathcal{E}, \mathcal{D}, \mathcal{T}, \mathcal{R} \rangle$ were one of the cognitive

systems in this equivalence class. If $E_i \in \mathcal{E}$ were an encoding process, then there is an $E_i+ \in \mathcal{E}+$ that is an equivalence class that contains E_i and all the equivalent E^*_i from other cognitive systems. Similarly, if $i_x \in \mathcal{I}$ were a unit then $i_x+ \in \mathcal{I}+$ would be an equivalence class that contained i_x. The equivalence-class system, CS+, differs from the individual CS just in that it is not committed to the structure of the encoding of the individual i_x+. Thus, this equivalence-class system abstracts away from the notational detail of the individual systems.

It is possible but not logically necessary that one could identify two subsets $\mathcal{I}_1+$ and $\mathcal{I}_2+$ of $\mathcal{I}+$ which we will call distinct representational types. They will be defined by non-identical subsets $\mathcal{E}_1+$ and $\mathcal{E}_2+$ of $\mathcal{E}+$, $\mathcal{T}_1+$ and $\mathcal{T}_2+$ of $\mathcal{T}+$, and $\mathcal{R}_1+$ and $\mathcal{R}_2+$ of $\mathcal{R}+$. Each i_x is a member of $\mathcal{I}_1+$ if it is only output by the encoding processes in $\mathcal{E}_1+$, if it is operated on by all and only the processes in $\mathcal{T}_1+$ and $\mathcal{R}_1+$. The corresponding assertion is true of all $i_x \in \mathcal{I}_2+$. It is possible, but not logically necessary that $\mathcal{I}+$ might be capable of being partitioned into two or more disjoint sets in this manner.

In contrast, it is possible that all processes might be defined on all $i_x \in \mathcal{I}+$ in which case the partition would not be possible. It is also possible that each i_x would have its own unique set of processes or that there may be a great many sets of very few members -- in either case, the partitioning would not be interesting. Thus, the possibility of partitioning $\mathcal{I}+$ into a small number of disjoint sets is an interesting empirical outcome. Furthermore, to determine that this interesting situation holds does not require one to decide which of the equivalence set of cognitive systems is the true one. Thus, it does not require that we decide how the information is represented (in terms of structure or notation). It only requires that we be able to identify which equivalence class of systems (i.e., which CS+) we are in. If we know that, we will know whether the human mind admits of an interesting sense of cognitive type.

Note that this argument does not guarantee that it will be possible to decide whether there are representational types. There may be two equivalence classes CS_i+ and CS_j+ which are not empirically discriminable. One equivalence class may have an interesting sense of cognitive type and the other may not. All this discussion does is show that current negative results about representational identifiability do not

eliminate the possibility of being able to establish that there are distinct cognitive types.

Appendix II

Table 6 provides a production set that will determine if two Shepard and Metzler figures are congruent. This production set is much more generally than the Shepard & Metzler task, however. It will decide whether any simultaneously presented pair of connected figures are congruent after rotation. Figure 15 illustrates the flow of control produced by the production system among the subgoals of the task. This production set assumes that the subject uses the stimuli as an external memory and is internally building an image in working memory. Figure 10 from earlier in the paper indicates where attention is focused in the external memory and what is currently being held in the internal working memory at various points during the correspondence.

Insert Table 6 and Figure 15 about here.

Decomposition into Sub-parts. Production P1 is the first to apply and simply transforms the goal from that of comparing the two objects to that of creating an image of one that is congruent to the other. It is assumed that the system can only operate on the primitive objects--i.e., the sub-sub-figures or arms in Figure 9. Therefore, much of the processing goes into decomposing the large structure into subunits. Production P2, which is next to apply, is one such decomposition. It selects a part of object1 (the upper elbow) to focus on and sets as the new goal to create an image corresponding to this part. The selection of the upper elbow rather than the lower one basically reflects a random choice. The next production to apply is P3 and it selects a part of object2 in the same locus and makes the new subgoal to create an image of this part corresponding to part1 of object1. Part (a) of Figure 10 illustrates where the system is at this point. It has chosen the two upper elbows of the objects to compare. Note these will not match. As Just and Carpenter document in their eye movement data, one of the problems with pairs that are not in similar orientation is that subjects will initially select the wrong ends to compare. Hochberg & Gelman (1977) also document the importance of "landmark features" to rotation of figures.

The two subparts focused upon contain subparts. Therefore, productions P2 and P3 will reapply a second time and focus attention on the top segments of each figure. At this point the system has focused down to the minimal parts of the representation and production P4 can apply which creates a copy of the focused part of

Table 6
A Production System for Rotating Shepard and Metzler Figures

P1: IF the goal is to compare object1 to object2
THEN set as the subgoal to create an image of object2 that is congruent to object1

P2: IF the goal is to create an image of object2 that is congruent to object1
and part1 is a part of object1
THEN set as a subgoal to create an image of a part of object2 corresponding to part1

P3: IF the goal is to create an image of a part of object2 corresponding to part1
and part2 is an untried part of object2 in locus A
and part1 is in locus A of object1
THEN set as a subgoal to create an image of part2 that is congruent to part1
and tag part2 as tried

P4: IF the goal is to create an image of object2 that is congruent to object1
and object2 has no subparts
THEN build an image of object2
and set as a subgoal to make the image congruent to object1

P5: IF the goal is to make image1 congruent to object2
and image1 and object2 do not have the same orientation
and the orientation of object2 is less than 180° more than the orientation of image1
THEN rotate image1 counterclockwise

P6: IF the goal is to make image1 congruent to object1
and image1 and object1 have the same orientation
and image1 and object1 do not match
THENPOP with failure

P7: IF the goal is to make image1 congruent to object1
and image1 and object1 match
THEN POP with success
and record that image1 is congruent to object1

P8: IF the goal is to create an image of object2 that is congruent to object1
and an image is congruent to object1
THEN POP with the result that image

P9: IF the goal is to create an image of object2 that is congruent to object1
and no congruent image was created
THEN POP with failure

P10: IF the goal is to create an image of a part of object2 corresponding to part1
and an image is congruent to part1
THEN POP with the result that image

P11: IF the goal is to create an image of a part of object1 corresponding to part1
and there are no more candidate parts of object2
THEN POP with failure

P12: IF the goal is to create an image of object2 that is congruent to object1
and there is an image of part2 of object2 that is congruent to part1 of object1
and part3 of object1 is attached to part1
and part4 of object2 is attached to part2
THEN build an image of part4
and set as the subgoal to attach to the image of part2 this image of part4 so that it is congruent to part3

P13: IF the goal is to attach image2 to image1 so that image2 is congruent to part3
and image1 is an image of part1
and image2 is an image of part2
and part2 is attached to part1 at locus-A
THEN attach image2 to image1 at locus-A
and set as a subgoal to test if image2 is congruent to part3

P14: IF the goal is to test if an image is congruent to an object
and the image and the object match
THEN POP with success

P15: IF the goal is to test if an image is congruent to a part
and the image and the object do not match
THEN POP with failure

P16: IF the goal is to attach image1 to image2 so that it is congruent to a part
and a subgoal has resulted in failure
THEN POP with failure

P17: IF the goal is to create an image of a part of object2 corresponding to part1
and part2 is an untried part of object2
THEN set as a subgoal to create an image of part2 that is congruent to part1
and tag part2 as tried

P18: IF the goal is to attach to image1 image2 so that it is congruent to part3
and this has been successfully done
THEN POP with the combined image1 and image2 as a result

P19: IF the goal is to create an image of object1 that is congruent to object2
and object2 is not primitive
and a successful image has been synthesized
THEN that image is of object2
and it is congruent to object2
and POP with the result that image

P20: IF the goal is to create an image of object2 that is congruent to object1
and an image1 of part2 of object2 has been created

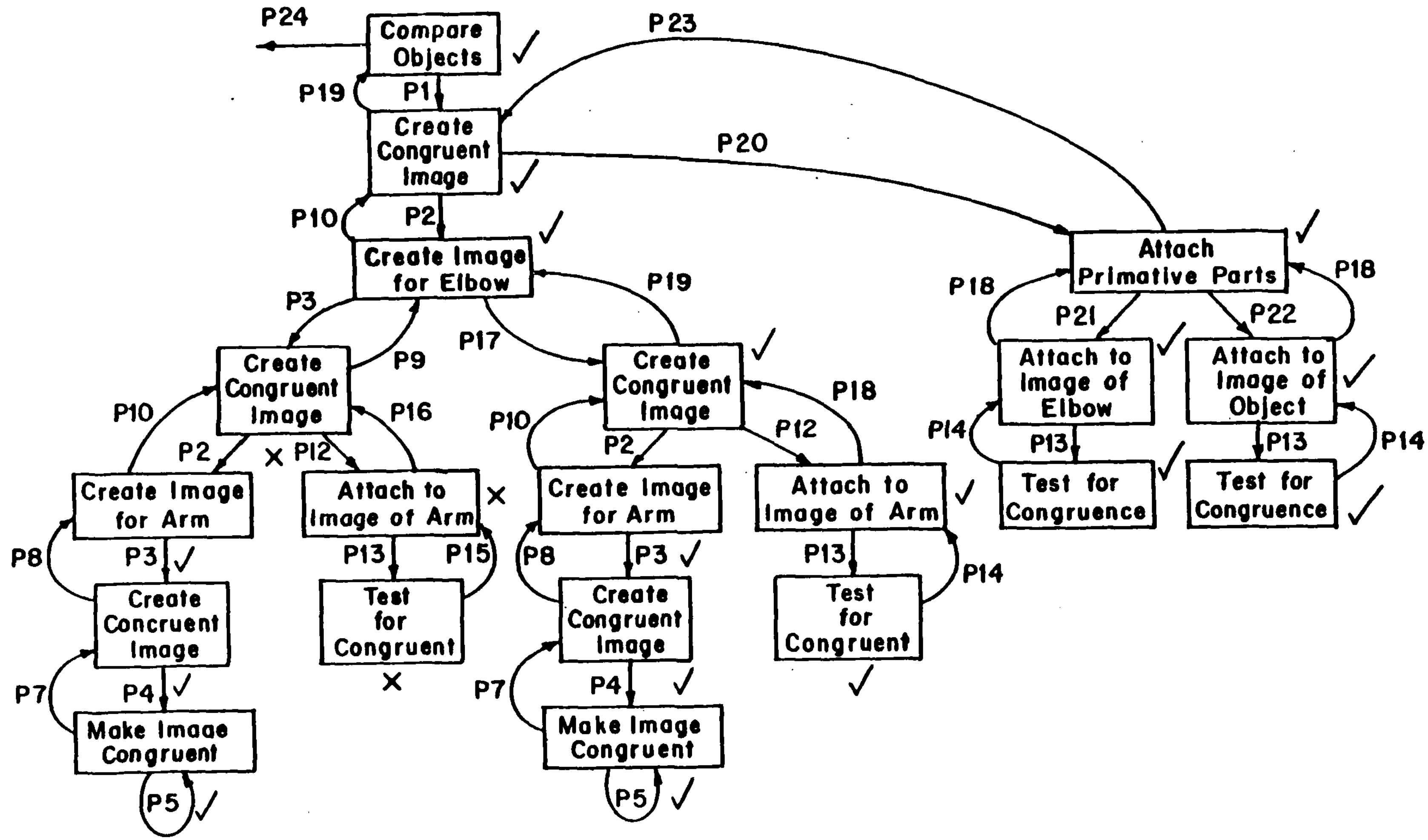
and the image is congruent to part1 of object2
and part1 is attached to part3
and part2 is attached to part4
and part4 is not primitive
THEN set as a subgoal to attach images of primitive parts of part4 to the
image so that they are congruent to part3

P21: IF the goal is to attach images of primitive parts of object2 to image1 so
that they are congruent to object1
and part2 is a primitive part of object2
and image1 is an image of object4
and part2 is attached to object4
and image1 is congruent to object3
and part1 is attached to object3
and part1 is a primitive part of object1
THEN build an image2 of part2
and set as the subgoal to attach image2 to image1 so that it is congruent to part1

P22: IF the goal is to attach images of primitive parts of object2 to image1 so
that they are congruent to object1
and image2 has been created of part2 of object2
and part2 is attached to part4 of object2
and image2 is congruent to part1 of object1
and part1 is attached to part3 of object1
THEN build image3 of part4
and set as the subgoal to attach image3 to image1 so that it is congruent to part3

P23: IF the goal is to attach primitive parts of object2 to image1 so that
they are congruent to object2
and all the primitive parts have been attached
THEN POP with the result being the synthesized image

P24: IF the goal is to compare object1 and object2
and an image of object2 has been created congruent to object1
THEN POP with the conclusion that they are congruent



P24
Compare Objects
P23
P19
P1
Create Congruent Image
P20
P10
P2
Create Image for Elbow
Attach Primative Parts
P3
P19
P18
P18
P21
P22
P17
P9
Create Congruent Image
Create Congruent Image
Attach to Image of Elbow
Attach to Image of Object
P10
P16
P10
P18
P14
P13
P13
P14
P2
P12
P2
P12
Test for Congruence
Test for Congruence
Create Image for Arm
Attach to Image of Arm
Create Image for Arm
Attach to Image of Arm
P8
P3
P13
P15
P8
P3
P13
P14
Create Concruent Image
Test for Congruent
Create Congruent Image
Test for Congruent
P7
P4
P7
P4
Make Imaae Congruent
Make Image Congruent
P5
P5

object2 and sets as the new subgoal to put this in congruence with the corresponding part in object1. Part (b) of Fig. 10 illustrates the situation at this point with the two upper arms focused and an image of part 2 created but not yet rotated into congruence with object1. Memory for object1 and object2 is being supported by the environment; working memory must maintain the image.

Rotation of Arms. *It is at this point that production P5 applies.* It matches on the fact that the images and the part of object1 do not have the same orientation and determines that a counterclockwise rotation will bring them into orientation. The action calls for this rotation. It is assumed that this production will produce a new image with a small adjustment in orientation. If the object part and the image part are not in correspondence, P5 will apply again and again until they are. When they have the same orientation, production P6 or P7 will apply. Therefore, a greater angle of separation will result in more applications of production P5. Production P6 matches when the image and the object have the same orientation but do not match. In the case of Shepard and Metzler block diagrams, this could only happen if the segments had different length. P7 applies when the image and object match.

In contrast to P1-P4, productions P5-P7 assume a number of processes which are only defined on images. They assume the ability to match the orientation of an image as an emergent property. They assume the ability to match one primitive image to another. This matching and the matching of the orientation assume an approximate process that will accept near equality. And of course, P5 assumes the ability to rotate images. (Implied in this is also an assumed ability to extract out the axis of rotation.) Thus, productions P5-P7 display quite clearly why imagery is a distinct representational medium in that it has its distinct processes. They also demonstrate that there is nothing contradictory between these distinct processes and a production system architecture. Note here, as elsewhere in the paper, there is no attempt to analyze the mechanisms used by the production system interpreter to produce the rotation. Again the literature abounds with proposals for subanalyses of imagery and it would be perfectly reasonable to pursue such an analysis within this framework. However, significantly, one does not need to make a commitment to such a subanalysis to conclude that imagery has distinct processes.

Detection of Mismatch. After some number of applications of P5 followed by a recognition of congruence by P7 the situation will be as illustrated in part (c) of Figure 10 with control returned to the goal of creating an image of the arm of object2 congruent to object1's arm. At this point P8 will recognize that this goal has been achieved and return to the higher goal of creating an image congruent to the top arm of object1. P10 recognizes this as successful and returns to the still higher goal of creating an image of the top elbow of object2 that is congruent to the top elbow of object1. The situation at this point is illustrated in part (d) of Figure 10: The system has refocused on the elbows and it has a rotated fragment of the second elbow.

At this point production P12 applies. Its condition matches due to the fact that a congruent image has been created for the end arm of the top elbow. It notes that there are a pair of attached subparts to match; it creates an image of the arm of object2 attached to the upper end arm and sets as a subgoal to attach that image to the existing image such that the resulting image is congruent to object1's upper elbow. Then production P13 applies; it notes where the two parts are attached in the object, and synthesizes a new image with the two subimages so attached. Part (e) of Fig. 10 shows the resulting situation. Note that this example illustrates the capacity for image synthesis.

Production P13 also sets the goal to determine if the new part of the synthesized subimage matches the corresponding part of object1. P15 will apply here because the image and sub-sub-part differ in length and will not match. This will POP failure back to the goal of attaching a congruent image to the initial image. Production P16 will then further POP failure back to the goal of creating an image of the top elbow object2 that is congruent to the top elbow of object1. Then production P9 POPs failure back to the goal of creating an image of a part of object2 congruent to the top elbow of object1.

Selection of Another Elbow. It is at this point production P17 applies to select the other end part of object2, the bottom part, to see if this can be put in congruence with the top part of object1. Part (f) of Figure 10 illustrates the situation at this point. The system is focused on the top elbow of object1 and the bottom elbow of object2. It is no longer maintaining the old image and it is about to create an image of the subpart. Then productions P2 and P3 apply to focus the system's attention on the end arms. As before P4 will create

an image--in this case of the bottom arm of object2. Then production P5 will rotate this image into congruence with the upper arm of object1. Then P7 will note that the image and object1's arm are congruent. The situation at this point is represented in part (g) of Figure 10. The system is focused on the two ends and has created an image of the object2 end rotated into congruence with the object1 end.

Then productions P8 and P10 apply to POP control back to the higher level goal of getting an image of the bottom elbow of object2 into congruence with the top elbow of object1. Production P12 applies next and sets the subgoal of attaching an image of the other arm in the bottom elbow of object2 to the image. P13 performs this operation and sets the goal to check whether the resulting image is congruent with object1.

The situation at this point is illustrated in part (h) of Figure 10. Production P14 recognizes that the new part of this synthesized subimage is congruent with object1 and returns success to the higher goal. Production P18 POPs control back to the goal of creating an image of the elbow. Production P19 recognizes that a successful image has been synthesized of the image of bottom half of object2 and that this is congruent to the top half. It POPs success back to the goal of finding some part congruent to the top half of object1. Then P10 POPs success back to the goal of establishing an image of object2 congruent to object1.

Attaching the Other Elbow. Then production P20 applies. It recognizes the fact that a partial image has been created and there is another non-primitive part of object2 (the top half) that needs to be imaged in congruence with the bottom half of object1. It sets as a subgoal to break this part of object2 into primitive parts and attach each of these to the existing image such that congruence is preserved. Production P21 then applies and selects the next pair of arms to process. It sets as the new goal to attach the upper interior arm of object2 to the image so that it is congruent with the lower interior arm of object1. The situation at this point is illustrated in Part (i) of Figure 10. Production P13 performs the attachment; production P14 confirms that congruence is preserved and production P18 returns control back to the goal of attaching primitive parts. The situation at this point is illustrated in part (j) of Figure 10. Next to apply is production P22 which creates an image of the remaining primitive part of object2 and sets as a subgoal to attach it to the image so that it is congruent to object1.

The situation at this point is illustrated in part (k) of Figure 10. Note that an image has been created of the top end arm of object2 but it has not yet been attached with the larger image. Production P13 performs this synthesis and P14 tests for congruence. P18 returns control back to the higher goal of attaching congruent subparts. P23 returns control from the goal of attaching primitive parts of the bottom half of object2. P19 next applies to recognize that a complete image of object2 has been synthesized congruent to object1 and returns control to the top level goal of comparing the objects. P24 concludes they are congruent because a congruent image has been created. The final situation is illustrated in part (l) of Figure 10 with a complete image of object2 created congruent to object1. Of course, with attention no longer focused on it the image will quickly fade from working memory. The typical experimental procedure also removes the two objects. The production set is then ready to respond to the next pair of stimuli.

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Figure Captions

Figure 1. The general architecture assumed in the ACT production systems.

Figure 2. A propositional representation of the string "The tall young man". Also represented is the information that young is stressed and that tall was pronounced "T + AH".

Figure 3. A string representation making explicit the type-token distinction. Also represented are substructure links giving part information and attribute links giving additional properties of the tokens.

Figure 4. Alternate notation for visual images. See text for discussion.

Figure 5. Procedure in Santa's experiment (1977). Subjects studied an initial array and then had to decide whether one of a set of arrays contained the same elements. Part A illustrates the geometric condition and part B the verbal condition.

Figure 6. Reaction times for Santa's experiment (1977) showing an interaction between type of material and test configuration.

Figure 7. Fruitface. See text for discussion.

Figure 8. Syntheses Problems. Combine the two figures in the two columns so the X's and O's overlap. What is the resulting image?

Figure 9. Decomposition of a Shepard and Metzler figure into subfigures and these into sub-sub-figures.

Figure 10. Various states of working memory during the processing of a pair of Shepard and Metzler figures. The shaded areas of the two objects represent focus of attention.

Figure 11. An example of a propositional network. See text for discussion.

Figure 12. A hypothetical hierarchical encoding in which the boxed units cannot be retrieved.

Figure 13. A tangled hierarchy of multiple representational types.

Figure 14. An illustration of how different representations can be processed by different systems to yield identical behavior.

Figure 15. The flow of control among goals in the production system of Table 3. Checks signify successful goals and X's unsuccessful goals.

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